Working Memory Capacity, Removal Efficiency and Event Specific Memory as Predictors of Misinformation Reliance

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Abstract

Event-related misinformation that has been retracted often continues to influence later reasoning regarding the event; this is known as the continued influence effect. To explain this effect, most research has focused on factors governing retrieval of the misinformation and its retraction from long-term memory. However, recent research has begun to investigate working memory (WM) capacity as a predictor of continued influence, based on WM's assumed role in information integration and updating following retraction encoding. The present study explored (1) whether memory for the materials more generally predicts continued influence, based on the notion that high-fidelity event representations may be easier to update, and (2) investigated the specific WM updating process of removal, testing whether participants' ability to remove information from WM would predict their susceptibility to continued influence. Latent-variable modelling suggested that memory for the materials but not WM capacity and removal efficiency were significant predictors of continued influence.

Keywords: Individual differences; Working memory; Removal efficiency; Event specific memory; Continued influence effect

Working Memory Capacity, Removal Efficiency and Event Specific Memory as Predictors of Misinformation Reliance

Event misinformation—defined here as causal event information initially believed to be true but subsequently found to be false—can often continue to influence people's reasoning even after a retraction or correction. This is known as the continued influence effect (CIE; Johnson & Seifert, 1994; Seifert, 2002; Wilkes & Leatherbarrow, 1988; for reviews see Chan, Jones, Hall Jamieson, & Albarracín, 2017; Lewandowsky, Ecker, Seifert, Schwarz, & Cook, 2012; Walter & Murphy, 2018). One real-world example of the CIE was seen during Australia's 2019/2020 "Black Summer" of bushfires. Despite reports of arson as a significant cause of the fires being repeatedly debunked (RMIT ABC Fact Check Unit, 2020), organizations such as the independent not-for-profit charity Crimestoppers continued to call for more scrutiny on arson in order to prevent further fires (e.g., issuing a media statement titled "Turn up heat on bushfire arsonists"; Crimestoppers, 2020). There are two main cognitive processes that have been theorized to underlie the CIE, namely selective retrieval and failures of information integration and memory updating.

The selective retrieval account proposes that continued reliance on misinformation occurs when people fail to retrieve a retraction alongside the misinformation (Ayers & Reder, 1998; Ecker, Lewandowsky, & Tang, 2010; Lewandowsky et al., 2012; Swire, Ecker, & Lewandowsky, 2017). An extension of this account assumes dual processes, specifically that strategic monitoring and control processes are necessary to prevent individuals from relying on automatically retrieved misinformation in their reasoning (Ayers & Reder, 1998; Ecker, Lewandowsky, & Tang, 2010). There is evidence that both misinformation familiarity and factors that impair strategic memory processes increase the CIE (Rich & Zaragoza, 2020; Swire et al., 2017).

The CIE has also been proposed to arise due to processes involved in information integration and memory updating. This account holds that in order for a retraction to be effective it must be integrated into a person's mental event model (Brydges, Gignac, & Ecker, 2018; Gordon, Brooks, Quadflieg, Ecker, & Lewandowsky, 2017; Rapp & Kendeou, 2007; Richter & Singer, 2017). Such integration, if successful, should entail the removal of outdated information, resulting in an updated, accurate model. As a retraction typically invalidates a key causal element of the event model, this threatens model coherence, which may lead to the retraction being poorly integrated. Therefore, if the retraction is not sufficiently integrated and the mental model updated, continued reliance on misinformation will occur. This account has been supported by findings that repeating misinformation explicitly within a correction enhances the effectiveness of the correction, presumably because the co-activation of misinformation and correction facilitates integration and updating (Ecker, Hogan, & Lewandowsky, 2017; Kendeou, Butterfuss, Kim, & van Boekel, 2019; Kendeou, Walsh, Smith, & O'Brien, 2014; Wahlheim, Alexander, & Peske, 2020).

Theoretically, if we assume that reliance on corrected misinformation is driven by people's ability to strategically monitor the output of their memory system or their ability to integrate information in working memory, and given that people vary in memory abilities, we should also expect that people will vary in their susceptibility to the CIE. Indeed, previous research has investigated and found inter-individual differences associated with CIE susceptibility. For example, De keersmaecker and Roets (2017) found that lower verbal intelligence was associated with greater reliance on corrected misinformation. Additionally, Jia, Shan, Xu, and Jin (2020) found WM processes, namely executive and updating processes, were negatively related to misinformation reliance. Of particular relevance for the present study, Brydges et al. (2018) reported that CIE susceptibility was related to working memory (WM) capacity.[1]

Working Memory

WM is a limited-capacity system responsible for the temporary storage and manipulation of information, including its integration and updating (Baddeley, 2000; Oberauer, 2002, 2009). WM is vital for a number of higher cognitive functions including reading comprehension, reasoning, and problem solving (Engle, 2002). Two aspects of WM that are of interest to this study are WM capacity and WM updating/removal.

Working memory capacity. WM capacity is an individual-differences construct reflecting the limited capacity of a person's WM, that is, the limited amount of information a person can hold for processing (Oberauer, Farrell, Jarrold, & Lewandowsky, 2016; Wilhelm, Hildebrandt, & Oberauer, 2013). Brydges et al. (2018) investigated whether WM capacity predicted susceptibility to the CIE, based on the assumption that WM capacity relates to the ease with which conflicting information can be integrated and an event model updated. Using latent-variable modelling, Brydges et al. found that WM capacity predicted continued reliance on misinformation; that is, lower WM capacity was associated with greater susceptibility to the CIE, independently of the effects of short-term memory capacity (STMC). By contrast, Brydges et al. failed to observe a unique predictive effect for STMC. Because a person's WM function will at least partially determine their ability to perform information integration, the relation between WM capacity and CIE susceptibility was taken as support for the integration/updating account of the CIE (also see Gordon et al., 2017).

[1] We note that people's more general susceptibility to believe (uncorrected) false information has also been investigated from an individual-differences perspective. Specifically, lower levels of analytic reasoning, need for cognition, WM capacity, intelligence, and perceptual abilities, as well as greater levels of delusion-proneness and dogmatism have been associated with increased belief in false information (Bronstein, Pennycook, Bear, Rand, & Cannon, 2019; Gerrie & Garry, 2007; Leding & Antonio, 2019; Pennycook & Rand, 2020; Swami, Voracek, Stieger, Tran, & Furnham, 2014; Zhu et al., 2010).

However, further research is needed to examine the role of WM for the CIE. Brydges et al. (2018) suggested that future work should examine WM processes beyond capacity, which provides a rather generic measure of WM functioning. Specifically, they suggested that the more specific WM process of removal might have a stronger relationship with the CIE.

Updating/removal. WM must be both stable and flexible; that is, information stored within WM must be protected against forgetting and interference from no longer relevant information, while still allowing modification or replacement of information when required (Ecker, Lewandowsky, Oberauer, & Chee, 2010; Kessler & Meiran, 2008; Oberauer, Lewandowsky, Farrell, Jarrold, & Greaves, 2012). An efficient WM updating mechanism is thus necessary to remove outdated information from WM in order to prevent interference, and to adapt to a changing environment and maintain a relevant, up-to-date understanding of the world. It has been suggested that a process of active, item-wise removal lies at the heart of WM updating (Ecker, Lewandowsky, & Oberauer, 2014; Ecker, Oberauer, & Lewandowsky, 2014; Oberauer et al., 2012; Singh, Gignac, Brydges, & Ecker, 2018).

The removal of irrelevant information has also been theorized to be a key contributor to the CIE: if a critical piece of information in a mental model is invalidated by a retraction, it must then be removed in order to maintain a coherent, up-to-date model (Brydges et al., 2018; Gordon et al., 2017; Kendeou et al., 2014; Singh et al., 2018). Given the integral role that removal plays in minimizing interference from irrelevant information and allowing processing of relevant information, it seems likely that removal will also play a role in the processing of misinformation corrections. Theoretically, greater removal efficiency should allow for a more coherent, better integrated mental model, with less interference from the outdated misinformation. A person's removal efficiency should thus predict their CIE susceptibility.

Ecker and colleagues (Ecker, Lewandowsky et al., 2014; Ecker, Oberauer et al., 2014) developed a WM updating task that allows for the reliable measurement of an individual's removal efficiency. In their task, participants remember a set of three items that is continuously updated (i.e., one item is replaced by a new item at each of multiple updating steps). Before each update, a cue is presented that indicates which item is about to be replaced. This cue is either presented long before the new item appears (long cue-target interval, CTI)—allowing time for the outdated, to-be-replaced item to be removed before the new item is encoded—or immediately before the new item (short CTI), allowing only enough time for attention to be directed to the to-be-updated item but no removal to take place. Ecker et al. found updating was faster following a longer CTI, suggesting the longer time was used for the removal of information from WM.

Singh and colleagues (2018) used an individual-differences approach to examine the relationship between removal efficiency and WM capacity. Theoretically, removal efficiency should be associated with WM capacity, as more efficient removal of irrelevant information should result in less interference and allow greater processing of relevant information and thus a greater effective WM capacity. Singh et al. did find a relation between removal efficiency and WM capacity, suggesting that the ability to remove information from WM is associated with WM capacity. They also found that removal ability was indirectly associated with fluid intelligence (gF) via its relation with WM capacity. The fact that gF itself has been discussed as a predictor of CIE susceptibility (De keersmaeacker & Roets, 2017) adds further weight to the hypothesis that there should be a relationship between removal efficiency and susceptibility to the CIE. It was the primary aim of this study to test this hypothesis.

Fidelity of the Event Representation

A secondary hypothesis pertains to participants' memory for the specific event, viz. the event report provided during the experiment. Misinformation research often includes measures to assess individuals' memory for and understanding of the materials in order to ensure adequate encoding (e.g., Ecker, Hogan et al., 2017). However, to the authors' knowledge, no study has assessed whether memory for the materials might be a unique predictor of susceptibility to the CIE. Theoretically, more thorough encoding of the materials should yield a more high-fidelity representation, which may aid integration and updating by facilitating conflict detection (Kendeou et al., 2014; Putnam, Wahlheim, & Jacoby, 2014; Stadtler, Scharrer, Brummernhenrich, & Bromme, 2013), thus resulting in a lower CIE. In line with this, Ithisuphalap, Rich, and Zaragoza (2020) found that reflecting on one's initial event model improves subsequent event-model updating, and argued this was due to stronger model coherence facilitating detection of inconsistencies between initial and superseding event reports. This notion is further supported by the finding that retractions that contain an explicit reminder of the misinformation are more effective, presumably because they highlight the incorrect information as a target for updating (Ecker, Hogan et al., 2017). Overall, this suggests that better encoding of materials may reduce misinformation reliance through more effective updating of the event model. While Ecker, Lewandowsky, Swire, and Chang (2011) found comparable CIEs in conditions that applied or did not apply cognitive load throughout encoding of the materials, they also did not find significant differences in memory for the materials across conditions, and did not specifically look at memory for the materials as a predictor variable.

The Present Study

The aim of the present study was to examine whether WM capacity, removal efficiency, and memory for the materials predicted susceptibility to the CIE. To this end, the study used an individual-differences approach. Participants completed WM capacity and WM updating task batteries (Brydges et al., 2018; Singh et al., 2018), followed by a CIE task that involved reading six event reports—some of which contained retractions—and answering a series of memory and inferential reasoning questions. We tested the relation of WM capacity, removal efficiency, and memory for the materials with susceptibility to the CIE through a latent-variable analysis, following the procedure of Brydges et al. (2018).

The study's independent variables were participants' WM capacity, removal efficiency, and their memory for the event reports (which we will refer to as "content span"). The dependent variable was misinformation reliance based on responses to post-manipulation inferential reasoning questions. There were four main predictions: It was predicted that (1) there would be a negative relationship between WM capacity and CIE susceptibility, such that greater WM capacity would be associated with lower misinformation reliance; (2) there would be a negative relationship between removal efficiency and CIE susceptibility, such that more efficient removal would be associated with lower misinformation reliance; (3) there would be a negative relation between individuals' content span and susceptibility to the CIE, such that better event-report memory would be associated with lower misinformation reliance. Finally, in line with Singh et al. (2018), we expected that WM capacity and removal efficiency would be related, but to some degree distinct constructs, as evaluated from a latent-variable perspective.

Method

Participants

A total of 401 undergraduate students from the University of Western Australia participated in the current research in exchange for course credit. Based on various a-priori outlier and minimum-performance criteria (see below), 93 participants were excluded from analysis, yielding a final sample of $N = 308$ participants (194 females, 111 males, 3 participants of undisclosed gender; mean age $M = 20.94$ years, $SD = 5.147$, range 17 to 51).

Materials

WMC task battery. The battery comprised three WM capacity tasks taken from Brydges et al. (2018), which were completed in a fixed order: symmetry span (SS), operation span (OS), and reading span (RS). All three tasks were complex span tasks comprising a primary memory task interleaved with a secondary processing task, and were completed via Inquisit 5 software (Millisecond, 2018). In the SS task, an abstract black and white image was presented on the screen and participants had to decide whether the image was vertically symmetrical or not. Following the symmetry judgment, a 4 × 4 square matrix appeared with a single square colored red. Participants had to remember the position of the red square, before completing another symmetry judgment. This sequence continued with the number of to-be-remembered red squares ranging between 3 and 7. Following this was a serial recall whereby a matrix appeared and participants had to click the relevant squares in the order that they were originally presented in. In the OS task, a mathematical equation (e.g., $2 \times 1 - 1$) and subsequent answer (e.g., 3) were presented, and participants had to indicate whether the answer was correct or incorrect (i.e., in the example, the correct response was "incorrect" because $2 \times 1 - 1 \neq 3$). In the RS task, participants were presented with a sentence and had to indicate whether the sentence was sensible (e.g., "I like to run in the park") or insensible (e.g., "I like to run in the sky"). Following these decisions in both OS and RS tasks, a single letter was presented on the screen, which had to be remembered. This judgment-letter sequence continued for 3-7 letters. The letters were recalled in order by making a selection from a matrix of 10 letters including both the target letters and distractors. At the end of each task, participants were given feedback on their performance. In total, for each task there were 15 trials (with three trials at each set size 3-7). See Redick et al. (2012) for more details regarding the tasks, and Supplementary Figure S1 for an illustration of the WMC tasks.

WM removal/updating task battery. The removal battery comprised three versions of the updating task developed by Ecker, Lewandowsky et al. (2014), using digits (0-9), letters (consonants), and words (neutral, monosyllabic, 3-5 letters in length), respectively. Tasks were run using JATOS (Lange, Kühn, & Filevich, 2015). All three tasks comprised encoding, updating, and recall phases. In the encoding phase, three black rectangular frames containing a set of three to-be-remembered items (either digits, letters, or words) were presented for two seconds. A series of updating steps then followed. Individual items were cued for updating by the frame turning red. The duration of the cue (the cue-target interval, CTI) was either short (200 ms) or long (1,500 ms); manipulation of the CTI varied the available time for removal, which allowed estimation of a person's removal efficiency (see Scoring for details).[2] The new item was then presented, and participants pressed the spacebar to indicate when they had encoded the new item and updated their memory; their response time was recorded. There were 1 to 21 updating steps per trial, with a constant 10% stopping probability after each step, resulting in an unpredictable sequence and thus equal incentive for participants to perform all updating steps. At the end of each trial, recall of the three items was cued with a question mark appearing randomly in each of the frames. There were 12 trials per task with an average of 9 updates per trial (i.e., approximately 108 updating steps in total, or 54 per CTI condition). See Singh et al. (2018) for more information. See Supplementary Figure S2 for an illustration of the WM removal/updating task.

Misinformation task. The misinformation task involved six fictional event reports detailing newsworthy events (e.g., a fish kill in a local river). The task was completed using Qualtrics software (Qualtrics, Provo, UT), and reports were taken from Brydges et al. (2018). Each report was separated into two short articles (approximately 100 words each), which were presented for a minimum of 15 seconds. The first article of each report contained a critical piece of information about the cause of the event (e.g., chemical waste dumping by a

[2] The cue-target intervals are in line with Ecker, Lewandowsky et al. (2014) and Singh et al. (2018). A justification for the CTI durations can be found in Ecker, Lewandowsky et al. (2014).

pharmaceutical company led to water contamination in the river and thus the fish kill). Three of the reports contained a retraction of the critical information, that is, participants were explicitly told the critical information was incorrect (e.g., it was clarified that tests disconfirmed chemical water contamination as the cause of the fish kill), while the remaining three reports contained no retraction. The reports were presented in a fixed order alternating no-retraction and retraction reports (i.e., NR1, R1, NR2, R2, NR3, R3). Order and assignment of retraction and no-retraction conditions to reports were not counterbalanced in order to reduce method variance. Following encoding of all reports, participants completed a distractor word sleuth task for one minute before answering a series of questionnaires. There was one questionnaire per report, and they were given in the same order as the reports. Each questionnaire had three multiple-choice memory questions targeting details mentioned in the report (e.g., "What water department was involved?") to measure report memory, as well as five inference questions to assess reliance on the critical information (following ample precedent; e.g., Ecker et al., 2017). Four of the inference questions were statements (e.g., "The riverside pharmaceutical company should start an internal investigation and review their procedures") that were rated on an 11-point Likert scale (0 "completely disagree" to 10 "completely agree"). The final inference question was a direct choice as to what caused the event (e.g., "What do you think was the cause of the fish deaths?" – a. Chemical spill; b. Water temperature; c. Virus; d. Algae bloom). See Supplement for all event reports, memory and inference questions.

Scoring

WMC scores. Partial credit unit scoring was used for all three WM capacity tasks tasks (i.e., participants received credit for partial recall of a set; e.g., recall of 3 out of 4 items was scored as 0.75 rather than zero as in absolute span scoring), in line with Brydges et al.

(2018) and recommendations by Conway et al. (2005). WM capacity task scores represented serial-recall performance on a continuous 0-1 scale.

Removal efficiency scores. Participants' removal efficiency was determined using a regression-residual score (as per Brydges et al., 2018; Ecker, Lewandowsky, et al., 2014; Singh et al., 2018), calculated as the individual residuals obtained from a simple linear regression model predicting the short-CTI RTs from the long-CTI RTs. On this score, more-negative values indicate greater removal efficiency.

Misinformation task.

Inference scores. As per Brydges et al. (2018), the inferential rating-scale responses were transformed onto continuous 0-1 scales, and the multiple-choice questions were scored as 0 or 1. For the latent variable analysis, three difference scores (no-retraction – retraction inference scores) served as the CIE dependent variables in the primary model.[3] A greater difference between conditions indicated less reliance on retracted misinformation and a smaller CIE. The score was multiplied by -1 so that a more negative score reflects less reliance on the misinformation.

Memory scores. The multiple-choice memory questions were scored as 0 or 1. The means of the three memory questions calculated separately for each event report served as the observed variables for the content span latent variable.

[3] While this is the most intuitive approach, the creation of three CIE difference scores requires arbitrary pairing of reports. Avoiding this was a reason for choosing a single-indicator approach in Brydges et al. (2018), which involved calculation of a single-variable indicator based on the average of these difference scores with the error variance ($1 – \alpha \times$ variance) and loading on the latent trait ($SD \times \sqrt{\alpha}$) calculated from the internal reliability and variance of the difference score. Here, results were identical regardless of how the reports were paired, and also when using the single-indicator approach. See the Supplement for the single-indicator model.

Procedure

Ethics approval was obtained from the University of Western Australia's Human Research Ethics Office. Prior to starting the experiment, participants read an approved information sheet and gave consent. Participants completed the tasks in a fixed order: WM capacity task battery (i.e., SS, OS, RS), WM updating/removal task battery (i.e., letters, digits, words), and finally the misinformation task. In total, the experiment took approximately 90 minutes.

Data Analysis

In the following, the latent variables associated with WM capacity, WM removal, and memory for the reports will be referred to as WMC, removal, and content span, respectively. In order to evaluate the WMC and removal latent variables for dimensional distinctness, a single-factor model was compared against a correlated two-factor (WMC and removal) model. Dimensional distinctness was considered given if the WMC and removal 95% upper-bound correlation confidence interval did not intersect with 1. In order to evaluate the potential influence of WMC, removal, and content span on CIE, the CIE latent variable was regressed onto the WMC, removal, and content span latent variables. The standardized beta weights associated with the WMC, removal, and content span latent variables were of key interest.

Based on guidelines summarized by Schweizer (2010), the models were deemed to be well-fitting according to the following criteria: Comparative fit index (CFI) $\geq .95$; Tucker-Lewis index (TLI) $\geq .95$; standardized SRMR $< .08$; and root mean square error of approximation (RMSEA) $< .06$. The 90% CIs of the RMSEA are also reported. The Bayesian information criterion (BIC) was used to compare models, with smaller BIC values indicating better fit. The implied model χ^2 statistics are also reported. All models were tested in Amos 25 (Arbuckle, 2017) via maximum likelihood estimation; however, the standard errors and confidence intervals were estimated via bias-corrected bootstrapping (with 2,000 replications), in order to help ensure robustness to any deviations from normality. Bayes factors were calculated in RStudio (RStudio Team, 2020), using the lavaan (Rosseel, 2012) and bain packages (Gu, Hoiktink, Mulder, & Van Lissa, 2020).[4]

Results

Statistical Procedures and Analysis

Data screening. A total of $N = 401$ participants completed all tasks; out of those, $n = 21$ were missing data for the RS task (due to a technical issue) and their RS scores were imputed based on age, OS, and SS variables. We applied three a-priori exclusion criteria: Participants were removed if (1) they scored below 70% correct on any secondary task in the WM capacity tasks ($n = 18$) or failed to correctly answer at least one memory question (out of three) for any report in the misinformation task ($n = 61$)[5]; this ensured participants adequately engaged with the materials; and (2) their recall performance in any WM updating task fell 3SDs above or below the condition-wise grand average ($n = 10$); this ensured they had engaged adequately in updating. Additionally, participants' RTs were trimmed (RTs < 300 ms and time-outs > 5s were excluded) to include only valid updating steps, and outlier responses were removed if they fell 3SDs above or below each participant's respective RT mean.

[4] Bayes factors (*BF*) represent the relative evidence for two competing hypotheses, given the data. *BF*s between 1-3 provide anecdotal evidence, a *BF* of 3-10 provides moderate evidence, a *BF* of 10-30 provides strong evidence, a *BF* of 30-100 provides very strong evidence, and a *BF* greater than 100 constitutes extreme evidence (Van Lissa et al., 2020; Wagenmakers et al., 2018).

[5] This a-priori criterion led to an unexpectedly large number of exclusions. We therefore also modelled the data after applying a more lenient criterion—correct response to 6/18 memory questions, or 1/3 on average per report—which reduced the overall number of exclusions by $n = 55$. Results were fully consistent with the results reported here, and are provided in the Supplement.

All observed scores were associated with distributions that were sufficiently normal for parametric analyses (skew < |2| and kurtosis < |9|; Schmider, Ziegler, Danay, Beyer, & Bühner, 2010; West, Finch, & Curran, 1995). Six scores across the observed variables were identified as outliers, based on the inter-quartile range rule with a 3.0 multiplier. Those six values were winsorized (increased or reduced to the next lowest/highest value not suspected to be an outlier; Tukey, 1962). Four multivariate outliers were identified when examining Mahalanobis distances (critical value of $p < .001$) and excluded from the analyses.

Descriptive Statistics

Descriptive statistics and correlations between WMC, removal, content span, and CIE variables are presented in Table 1.

Two manipulation checks were performed. The first check was done to ascertain a difference in updating RTs between the two CTI conditions in the updating tasks. Descriptive statistics for the short and long CTI conditions are presented in Table 2. Paired sample *t*-tests confirmed significant differences between short and long CTI conditions for the digit, letter, and word tasks, in the expected direction; all ts(307) > 19.31, $p < .001$.

Second, a manipulation check on the misinformation scores was conducted by calculating average no-retraction ($M = -.70$, $SD = .13$) and retraction ($M = -.57$, $SD = .22$) inference scores for each participant. There was a significant difference between conditions in the expected direction, $t(307) = 9.08$, $p < .001$, Cohen's $d = .52$.

Table 1

Descriptive Statistics and Correlations of Working Memory, Removal, and Misinformation Tasks.

Task	1.	2.	3.	4.	5.	6.	7.	8.	*M*	*SD*	Skew	Reliability
1. OS	–	.83	.52	-.23	-.15	-.04	.05	-.05	.86	.11	-1.32	.747
2. RS	.66***	–	.42	-.07	-.12	-.04	.05	-.09	.81	.15	-1.23	.835^
3. SS	.39***	.33***	–	-.21	-.17	.05	.10	.10	.60	.15	.12	.753
4. Letters	-.14*	-.05	-.13*	–	.93	.84	.06	.10	1.23	146.37	.42	.494
5. Digits	-.11	-.09	-.12*	.53***	–	.79	.14	.03	-1.48	132.63	.41	.654
6. Words	-.03	-.03	.03	.45***	.49***	–	.18	-.13	-3.04	148.86	.13	.586
7. Content Span	.03	.03	.07	.03	.09	.11*	–	-.65	.82	.13	-.57	.631
8. CIE	-.03	-.06	.06	.05	.02	-.07	-.35***	–	-.37	.72	-.17	.460

Note. OS, operation span; RS, reading span; SS, symmetry span; CIE, CIE mean difference score; $N = 308$, ^ based on $n = 287$ due to missing RS data; * $p < .05$, ** $p < .01$, *** $p < .001$; correlations below the main diagonal are observed score correlations; for clarity and thoroughness we also report correlations attenuated for imperfect reliability (true score correlations) above the main diagonal (in line with Brydges et al., 2018; note these were not used in the SEM). The *M*s for the OS, RS, and SS tasks were based on serial recall performance in the tasks. The *M*s for the letter, digit, and word updating tasks were based on regression-residual scores, calculated as the individual residuals obtained from a simple linear regression model predicting the short-CTI RTs from the long-CTI RTs. The *M* for the content span task were based on the mean of the three memory questions calculated separately for each event report. The *M* for the CIE was based on the mean of the three difference score between no-retraction and retraction conditions.

Table 2

Response Times (in ms) for Short and Long CTI conditions for Letter, Digit and Word Tasks.

	Short CTI		*Long CTI*	
	M	*SD*	*M*	*SD*
Letters	1344.99	402.81	1141.98	383.13
Digits	1015.16	370.97	860.590	353.53
Words	1220.45	440.35	1032.04	419.57

Latent Variable Analyses

First, three basic measurement models (one for WMC, one for removal, one for content span) were tested. The WMC and removal measurement models were defined by three observed variables (WMC: OS, RS, SS; Removal: letter, digit, word). The content span measurement model was defined by six observed variables (average of the three memory questions for each of the six articles). The WMC latent variable had significant positive standardized loadings from all three WMC tasks; all *p*s < .001. This indicated that these three tasks measured a common WM capacity factor. The three removal tasks all had significant positive standardized loadings on the removal latent variable; all *p*s < .001. This indicated that the three removal tasks measured a common removal factor. Similarly, the content span latent variable had significant positive standardized loadings from all six observed variables; all *p*s < .05. This indicated that these six tasks measured a common memory factor.[6]

Next, a single-factor WMC/removal model was tested. This model was found to be associated with unacceptable model-fit, $\chi^2(9) = 212.216$, $p < .001$, CFI = .535, TLI = .224, SRMR = .182, RMSEA = .271 (90% CI [.240, .303]), BIC = 280.977. Thus, the inter-

[6] The content span measurement model was found to be associated with good model fit, $\chi^2(9) = 14.082$, $p = .119$, CFI = .973, TLI = .956, SRMR = .038, RMSEA = .043 (90% CI [.000, .084]), BIC = 82.843. Model fit could not be quantified for the WMC and removal measurement models, as they were associated with zero degrees of freedom.

associations between the WMC and removal observed test scores should not be considered representative of a single cognitive construct. By contrast, a correlated two-factor measurement model was found to be associated with excellent model fit, $\chi^2(8) = 12.957$, $p = .113$, CFI = .989, TLI = .979, SRMR = .034, RMSEA = .045 (90% CI [.000, .088]), BIC = 87.448. The WMC and removal latent variable correlation was estimated at $r = -.15$, 95% CI [-.30, .00], $p = .043$. Additionally, the TLI difference score indicated practical improvement in model fit for the correlated two-factor model, ΔTLI = .755 (see Gignac, 2007). This established that WMC and removal latent variables reflect two different constructs.

Bivariate correlations between the CIE latent variable and WMC, removal, and content span, were estimated. The WMC-CIE ($r = -.07$ [-.24, .12], $p = .439$) and removal-CIE ($r = .03$ [-.21, .23], $p = .740$) latent variable correlations were both non-significant. The content span-CIE latent variable correlation was significant ($r = -.61$ [-.82, -.40], $p = .014$).

Latent-variable modelling. Although the content span latent variable was the only one of the hypothesized predictors to correlate significantly with the CIE latent variable, the planned multiple regression was, nonetheless, conducted to rule out the possibility of suppressor effects (Rucker, Preacher, Tormala & Petty, 2011). Specifically, a multiple regression latent-variable model was tested with WMC, removal, and content span as predictors of CIE. The model was found to be associated with excellent model fit, $\chi^2(86) = 96.496$, $p = .206$, CFI = .985, TLI = .982, SRMR = .047, RMSEA = .020 (90% CI [.000, .038]), BIC = 291.320. As can be seen in Figure 1, both WMC (ß = -.02 [-.18, .14], $p = .812$, $BF_{01} = 10.11$) and removal (ß = .08 [-.13, .27], $p = .413$, $BF_{01} = 5.59$) were associated with non-significant standardized beta weights. For WMC and removal, the Bayes factors suggested that the data were approximately 10 times and 5 times, respectively, more likely to occur under a model that excluded WMC and removal as predictors of the CIE, in comparison to a model that included WMC and removal as predictors of the CIE. By contrast, content span was associated with a significant standardized beta weight, ß = -.61 [-.82, -.40], p = .013, BF_{10} = 1356.85. The content span Bayes factor suggested the data were approximately 1356 times more likely to occur under a model that included content span as a predictor of the CIE, in comparison to a model that excluded content span as a predictor of the CIE. As to-be-expected, the WMC and removal latent variable correlation was virtually identical to the two-factor model, and estimated at r = -.15 [-.30, -.01], p = .042. The squared multiple correlation for CIE was estimated as R^2 = .383 [.16, .66], p = .002. Thus, 38% of the true score variance in CIE was accounted for by the model that included WMC, removal, and content span as predictors of CIE. We acknowledge that alternative ways of modelling the data exist. An alternative model, using separate retraction and no-retraction latent variables, is presented in the Supplement.

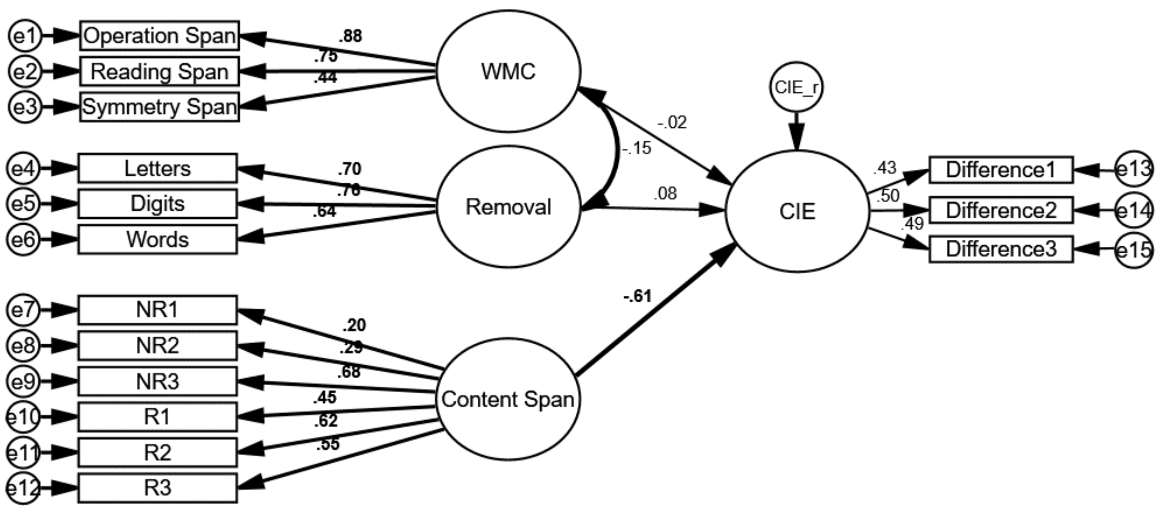

Figure 1. Structural equation model of working memory capacity (WMC), working memory removal (Removal), and content span predicting the continued influence effect (CIE). Straight lines with single arrows are regression paths. Curved lines with double arrows are correlations. Emboldened lines and values indicate statistically significant regression/correlation coefficients (p < .05). e1-13 = error variables. CIE_r = residual error associated with the CIE latent variable; coefficients in bold were significant statistically (p < .05).

Revisiting Brydges et al. (2018). In order to potentially replicate the effects reported in the previous analysis, we added the content span variable to the Brydges et al. (2018) modelling ($N = 216$). Brydges et al.'s study used working memory capacity (WMC; measured with the same three tasks as in this study) and short-term memory capacity (STMC; measured with three simple-span tasks) as predictors of CIE susceptibility. The Brydges et al. study also contained three multiple-choice memory questions for each report, allowing the inclusion of content span as an additional latent variable. Brydges et al. found that WMC had a significant unique effect onto the CIE (ß = -.36, $p = .013$), whereas STMC did not (ß = .22, $p = .187$). Note again that Brydges et al. used a single CIE indicator approach, which we followed here to keep models as comparable as possible (results were equivalent with the three-indicators approach).

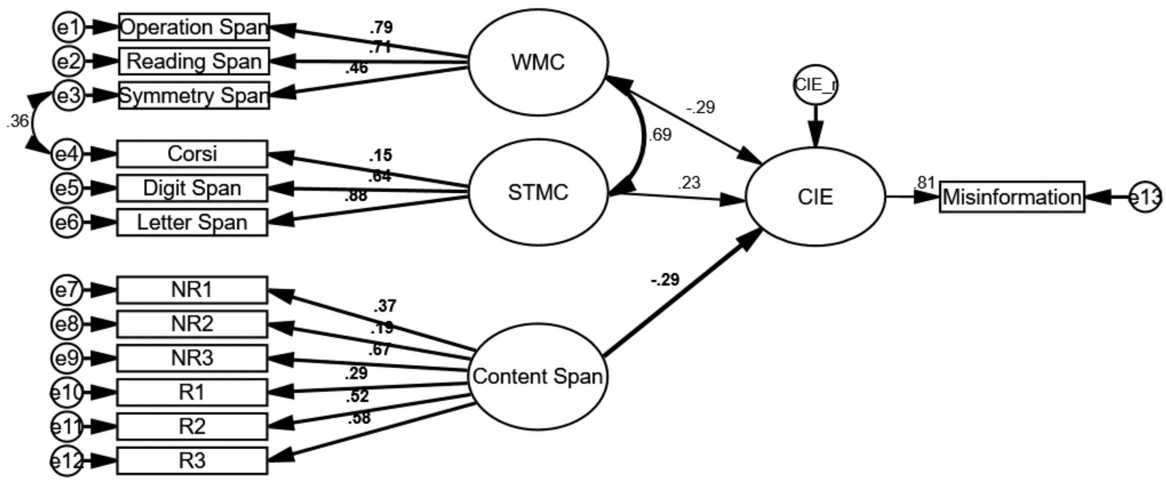

Figure 2. Structural equation model of working memory capacity (WMC), short term memory capacity (STMC), and content span predicting the continued influence effect (CIE). Straight lines with single arrows are regression paths. Curved lines with double arrows are correlations. Emboldened lines and values indicate statistically significant regression/correlation coefficients ($p < .05$). e1-13 = error variables. CIE_r = residual error associated with the CIE latent variable; coefficients in bold were significant statistically ($p < .05$).

The newly tested model included WMC, STMC, and content span as predictors of CIE. The model was found to be associated with acceptable model fit, $\chi^2(61) = 88.915$, $p = .011$, CFI = .936, TLI = .919, SRMR = .091, RMSEA = .046 (90% CI [.023, .066]), BIC = 250.173. As can be seen in Figure 2, both WMC (ß = -.29 [-.63, -.02], $p = .073$, $BF_{01} = 3.28$) and STMC (ß = .23 [-.04, .56], $p = .141$, $BF_{01} = 3.36$) were associated with non-significant standardized beta weights. For WMC and STMC, the Bayes factors suggested that the data were approximately three times more likely to occur under a model that excluded WMC and STMC as predictors of the CIE, in comparison to a model that included WMC and STMC as predictors of the CIE. By contrast, content span was associated with a significant standardized beta weight, ß = -.29 [-.50, -.05], $p = .015$, $BF_{10} = 1.23$. The content span Bayes factor suggested the data were approximately one times more likely to occur under a model that included content span as a predictor of the CIE, in comparison to a model that excluded content span as a predictor of the CIE. The WMC and STMC latent variable correlation was estimated at $r = .69$ [.56, .83], $p < .001$. The squared multiple correlation for CIE was estimated as $R^2 = .128$ [.03, .27], $p = .006$. Thus, 12% of the true score variance in CIE was accounted for by the model that included WMC, STMC, and content span as predictors of CIE. Thus, Brydges et al.'s (2018) finding that WMC was a significant, unique predictor of CIE susceptibility was not replicated when taking content span into account; rather, the results were consistent with the results obtained from our new sample. See Supplement for alternative model results using separate retraction and no-retraction latent variables.

Discussion

The aim of this study was to examine whether an individual's WM capacity, removal efficiency, and memory for the materials predicted susceptibility to the continued influence effect of misinformation (CIE). It was predicted that there would be a negative relationship between CIE susceptibility and (1) WM capacity, (2) removal efficiency, and (3) memory for the event reports, respectively. It was also expected that (4) WM capacity and removal efficiency would be related but separable constructs. The first two hypotheses were not supported. However, we found that memory for the event reports was a significant predictor of CIE susceptibility, and that WM capacity and removal efficiency were significantly related. Each of the results will be reviewed before discussing theoretical implications and limitations.

Effect of the Retraction

Firstly, this study found that a retraction was effective in reducing, but not eliminating, reliance on the critical information compared to a no-retraction condition. This is consistent with previous research, which has documented the (partial) effectiveness of retractions (Ecker, O'Reilly, Reid, & Chang, 2020; Johnson & Seifert, 1994; Lewandowsky et al., 2012; Paynter et al., 2019; Rich & Zaragoza, 2016; Walter & Murphy, 2018).

Working Memory Capacity

The integration/updating account of the CIE proposes that post-retraction misinformation reliance results from a failure to integrate a retraction and subsequently update the mental model. As such, WM capacity was predicted to influence the ease with which this can occur, with support from previous research (Brydges et al., 2018). However, the current study failed to find a significant relationship between WM capacity and the CIE. While this result appears inconsistent with Brydges et al. (2018), a re-analysis of the Brydges et al. data suggested that the significant, unique effect of WM capacity in their study was rendered non-significant when controlling for individual differences in content span. Such an observation is essentially consistent with the results obtained from the new sample of data analyzed in this investigation. Thus, we can suggest that WM capacity may not have a unique role in predicting susceptibility to the continued influence effect. Assuming mental-model integration is a process that takes place in WM, this provides some evidence against the theoretical integration/updating account of the CIE.

Removal Efficiency

In addition to WM capacity, removal efficiency—the ability to remove outdated information from memory—has been theorized to play a role in the CIE (Brydges et al., 2018; Gordon et al., 2017; Kendeou et al., 2014; Singh et al., 2018). In contrast to our hypothesis, the current study found no relationship between removal ability and the CIE. This is the first study to investigate removal efficiency in the context of the CIE, and the null effect suggests that the ability to remove outdated information from WM does not play a significant role in the CIE. This finding also has implications for theoretical explanations of the CIE, as it again provides some evidence against the integration/updating account—theoretically, if integration/updating is important to the CIE, then one's ability to remove outdated information from a mental model in WM should aid in integration and model updating and lower misinformation reliance. This finding therefore favors the selective retrieval account of the CIE, which places stronger emphasis on LTM retrieval processes.

Fidelity of the Event Representation

The current study found memory for the event reports was a significant, unique predictor of CIE susceptibility, independently of WMC and removal efficiency. This novel finding may be interpreted in support of either integration/updating or selective retrieval accounts. On the one hand, proper encoding of the materials will create a higher-fidelity mental model, which may be easier to modify and update successfully, potentially by allowing better alignment and co-activation of misinformation and correction—a factor known to facilitate updating (Ecker, Hogan et al., 2017; Kendeou et al., 2014, 2019). On the other hand, the finding can also be interpreted in line with the selective retrieval account, as a person with generally stronger encoding of the materials is also more likely to have a strong representation not only of the misinformation but also the retraction, which should make it easier to recall the retraction later. It must be noted here, however, that a number of studies have found that memory for the correction is not an influential factor for the emergence of a continued influence effect (e.g., Ecker et al., 2011; Ecker, Lewandowsky, Tang, 2010). While content span, to the extent that it measures the fidelity of the event model, cannot be measured independently of the CIE task, future research could investigate whether individuals with generally poorer episodic memory are more susceptible to the CIE, in order to establish whether general memory ability or simply the fidelity of the mental model (i.e., the overall strength of encoding of the materials) predicts CIE susceptibility. Memory ability has been investigated in the post-event misinformation literature, albeit with mixed findings (e.g., Farina & Greene, 2020; Patihis et al., 2013). It may also be that the significant effect of content span is due its relation with verbal ability, which has been found to predict CIE susceptibility (De keersmaecker & Roets, 2017). Further research is needed to disentangle the possible relation between content span, verbal ability, and CIE susceptibility.

The Relationship between WMC and Removal Efficiency

Consistent with previous research by Singh et al. (2018), this study found a significant relationship between WM capacity and removal efficiency using the same task batteries. While studies by Ecker et al. (Ecker, Lewandowsky, Oberauer et al., 2010; Ecker, Lewandowsky et al., 2014) failed to find an association between WM capacity and removal ability, these studies used only a single updating task, which arguably provides a less reliable and valid measure compared to a battery of tasks, and, as such, future research should employ a battery of tasks to measure removal ability. This result is in line with previous research and computational models of WM (e.g., SOB-CS; Oberauer et al., 2012), which have proposed a relationship between WM capacity and removal, suggesting that more efficient removal of irrelevant information allows increased focus on relevant information, thus resulting in greater effective WM capacity (Ecker, Lewandowsky et al., 2014; Oberauer et al., 2012; Singh et al., 2018).

Limitations and Future Research Directions

This study has a number of limitations. Firstly, the sample used was made up entirely of undergraduate university students, which resulted in a largely homogenous sample, particularly in terms of cognitive ability and age. Previous research has shown that people with higher cognitive ability are less likely to rely on outdated information and thus are less susceptible to the CIE (De keersmaecker & Roets, 2017). Age has also been associated with belief in false information and thus may be an important factor in predicting susceptibility to misinformation, although there have been inconsistencies regarding the presence and direction of these effects (Baum et al., 2020; Brashier & Schacter, 2020; Roozenbeek et al., 2020). As such, future research could use a more heterogeneous general community sample, which may increase the likelihood of finding significant relations amongst the variables. Secondly, the reliability of the CIE difference score was low, which would be expected to yield less stable estimated effects between the latent variables (Kretzschmar & Gignac, 2019). Low reliability may be due to the small number of inference questions per report, and as such future research should focus on building more comprehensive measures of the CIE, for example, by including additional inference questions and/or an additional number of event reports, which may improve reliability. As the removal and content span measures were also associated with low reliability, further research with more reliable test scores may help find significant effects.

While this study only investigated WM capacity, removal, and content memory, it is important to note that other traits may also influence the CIE. As such, future research may wish to investigate additional predictors of misinformation susceptibility. For example, previous research has found an association between fluid reasoning and both WM capacity

(Colom, Rebollo, Palacios, Juan-Espinosa, & Kyllonen, 2004; Conway et al., 2002; Engle et al., 1999; Singh et al., 2018; Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002) and removal ability (Chen & Li, 2007; Friedman et al., 2006; Shipstead, Harrison, & Engle, 2016; Singh et al., 2018). As mentioned previously, De keersmaeker and Roets (2017) found a link between verbal intelligence and the CIE; however, the verbal intelligence measure they used was relatively narrow (i.e., one measure of vocabulary). Therefore, an additional investigation into the role of verbal intelligence in predicting CIE susceptibility is warranted, using a more comprehensive representation of verbal intelligence. Research has also identified cognitive style and susceptibility to cognitive biases as predictors of false beliefs (e.g., Bronstein et al., 2019; Stanovich & West, 1997; Swami et al., 2014); these could therefore also be investigated as predictors of CIE susceptibility. Moreover, given the significant content span finding in the present study, future investigations into relations between CIE and other variables should consider taking memory for the materials and general episodic memory ability into account.

Conclusion

Continued reliance on corrected misinformation can have negative implications for not only the individual but also society (e.g., Lazer et al., 2018). As such, an understanding of what factors may predict such reliance is important. The current study investigated whether an individual's WM capacity and removal efficiency would predict a person's susceptibility to the continued reliance on misinformation. The study failed to replicate a previous finding of a significant relationship between WM capacity and CIE susceptibility, and also found no significant effect for removal. This provides some evidence against the theoretical account that continued influence of misinformation arises primarily from failures of information integration and memory updating. Memory for the materials was a unique predictor of misinformation susceptibility, which suggests that high-fidelity event representations may be easier to update, or that general episodic memory abilities predict susceptibility to continued influence.

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Data availability: The data are available at https://osf.io/uvw5n/ (doi: 10.17605/OSF.IO/UVW5N).

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Supplement

WMC task battery

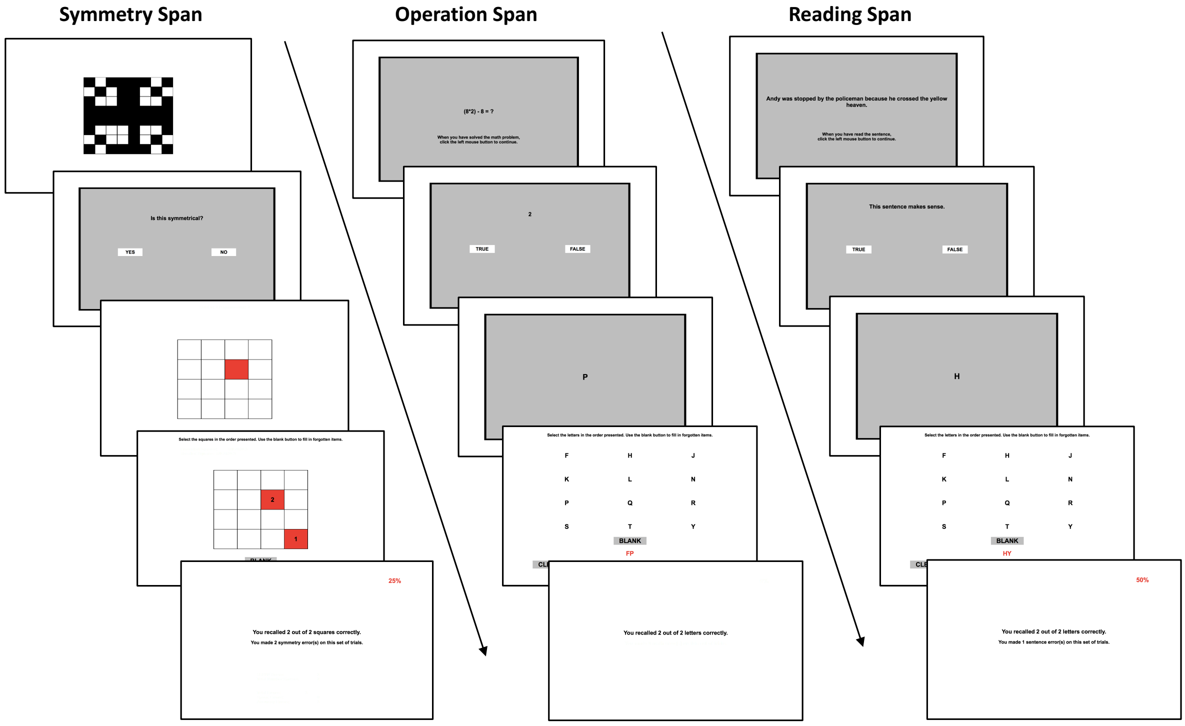

Figure S1. Example screenshots from symmetry, operation, and reading span tasks of the WMC task battery. Adapted with permission from *European Journal of Psychological Assessment* 2012; Vol. 28(3):164-171. © 2012 Hogrefe Publishing; www.hogrefe.com; doi:10.1027/1015-5759/a000123

WM removal/updating task

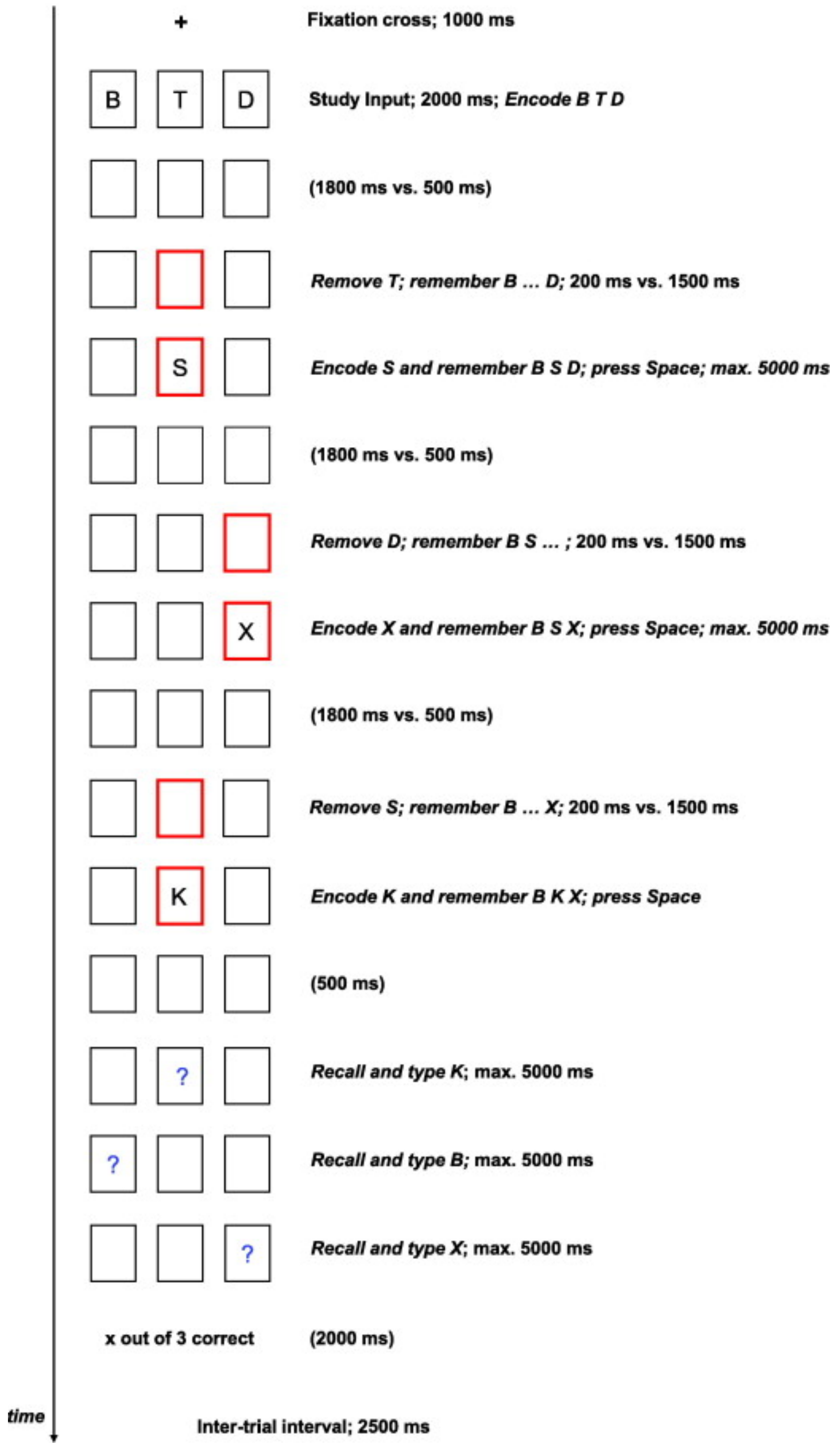

Figure S2. A trial sequence of the WM removal/updating task battery. The example trial features 3 updating steps. Reprinted with permission from *Journal of Memory and Language*, *74*, Ecker, U. K. H., Lewandowsky, S., & Oberauer, K., Removal of information from working memory: A specific updating process, 77-90, Copyright Elsevier (2014).

Event Reports

NR1—Airplane landing.

Article 1. Passengers on a commercial flight en route to Los Angeles received a terrible fright yesterday as their plane required an emergency landing. Peter Fern, the pilot of the aircraft, made the decision to land after he was having difficulties controlling the plane. The Federal Aviation Administration believes the pilot made the right decision, and attributed difficulties controlling the aircraft to a fault caused by extreme weather conditions. The aircraft was able to make a safe landing at Kansas City airport, and all 350 passengers on board were evacuated without problem. The aircraft involved was an A380 Airbus, the largest passenger airplane in the world.

Article 2. Passengers on a commercial flight that had to make an emergency landing at Kansas City airport were forced to stay overnight while the airline arranged a suitable replacement aircraft. Marie Scott, a passenger on the flight, told reporters of her ordeal: "It was horrible, all loose items were getting thrown around the cabin, and the seatbelt was hardly containing me. I'm glad I'm safe, but I just really want to go home to my family now." Meanwhile, the airport provided passengers with accommodation and complimentary food on behalf of the airline. In the morning, a replacement aircraft had been organized and passengers expressed their gratitude to the airline for managing the situation professionally.

R1—Bushfire.

Article 1. Firefighters in rural Victoria have been battling a bushfire that raged out of control in the state's North overnight. The bushfire came dangerously close to homes in the town of Euroa, but it is believed that no damage was caused to property. David Karle of the Country Fire Authority (CFA) indicated that authorities were looking into the cause of the fire, with initial evidence suggesting that the fire had been deliberately lit. Emergency services were still working tirelessly this morning to extinguish the flames, but were confident that the fire was unlikely to pose any further threat to local communities. The suspected burn area is estimated to be roughly 50,000 hectares.

Article 2. After working throughout the day, firefighters have managed to bring a bushfire in Northern Victoria under control. There have been no reported casualties or damage to property, with most land damage occurring in rural fringe areas and nearby forest reserves. After further investigation, authorities believed the fire had not been caused by arson. When speaking to the media, Euroa resident Casey Haas expressed her relief that no one had been harmed by the fire, and said she felt lucky that they had avoided disaster. Even so, she appealed to residents of the community to work together to ensure they were prepared for disaster if it ever struck again.

NR2—Death of a drug dealer.

Article 1. The death of a notorious drug dealer, known on the street as 'Coach', is being treated as suspicious. He had been under investigation for several months by police regarding his alleged involvement in the trade of methamphetamines. At this stage of the investigation, authorities believe the death was the result of an assault in what appears to have been a drug deal gone wrong, and various members of the local drug scene are being investigated. A neighbour discovered the man in his Frankston home during the early hours of Saturday morning. The man had been dead for several hours before he was found. Sergeant Barry Wade from the Victorian Police Force has asked anybody who has witnessed any suspicious behaviour in the area to contact authorities.

Article 2. A clandestine drug lab has been discovered in the home of a drug dealer who died last week at his Frankston home. Methamphetamines and cash, as well as a surveillance camera system, have been seized from the property. Some members of the local community have been sighted at the drug-dealer's home leaving flowers and paying their respect. The funeral is scheduled for tomorrow afternoon, and will be attended by friends and family of the deceased under police observation. A spokesperson for the family said they were extremely upset by their family member's death.

R2—Nightclub.

Article 1. A 21-year-old woman has been taken to St. Mary's hospital after losing consciousness whilst out partying at the Cable nightclub in London in the early hours of the morning. A friend of the woman said she had complained of hallucinations and nausea not long before falling unconscious. The woman's blood pressure and heart rate have stabilized and doctors believe the woman's symptoms were the result of her drink getting spiked. A recent series of drink- spiking incidents at local nightclubs has led to renewed calls for the introduction of a bottled- drinks-only policy. The incident comes as a reminder to party-goers to be careful with their drinks and always stay with friends.

Article 2. A woman who fell unconscious while partying at a London nightclub has remained in hospital. The woman was out celebrating with friends after graduating from the Regent Fashion Academy when she collapsed and required medical attention. Hospital doctors have now ruled out drink-spiking as the cause of her symptoms. Further tests were being conducted, but the woman was due to be released from hospital later today. The woman's brother stated the family was relieved that she was recovering well, and praised her friends, saying it was their timely aid that saved her from further harm. The woman herself has no memory of the incident.

NR3—Train derailment.

Article 1. A commuter train was derailed earlier this morning near the town of Metz in northern France. The accident occurred around 8.30am during the busy commuting period. Initial reports suggest that as many as twenty passengers may have lost their lives, and more than 100 people sustained injuries. It appears the train was travelling at excessive speed around a sharp bend of the track. Emergency services were called in from neighbouring Germany to assist with the recovery efforts. The injured were brought to local hospitals, and the train line between Metz and Thionville has been closed until further notice. Replacement buses will be available, but commuters have been urged to seek alternative arrangements if possible.

Article 2. The official death toll of the train derailment in northern France has now been put at 19. Among the deceased were French, German, and Swiss nationals, including the CEO of French food manufacturer Carmigel. A passenger explained that there had been no warning signs: “All of a sudden things and people were flying through the air. There was this moment of silence and weightlessness before a horrible bang and the sound of screeching metal. It was terrifying.” Closer analysis revealed that there had been a number of near-miss incidents on the affected section of tracks in recent years. The line will remain closed for a number of days while the site is cleared.

R3—Fish kill.

Article 1. The Freemont Water Department has been forced to shut down intake from its main water supply, the Denroy River, due to large scale fish deaths in the waterway. The department supplies water to the entire Shelby region. It is believed that the fish deaths were due to contamination caused by dumping of chemical waste by a riverside pharmaceutical company, in violation of the Missouri Clean Water Act. The water department stated it remained committed to ensuring that customers can be confident that their water supply is of the purest quality. Authorities have begun clearing the dead fish from the waterway.

Article 2. Authorities have been given the all-clear to continue water intake from the Denroy River, after operations had ceased for 5 days due to a fish kill in the waterway. The incident had residents concerned and occupied local news headlines all week. Tests by both the local water department and an independent agency have now disconfirmed a chemical spill as the cause. The water-intake shutdown was a critical issue for the region, as recent draught periods have resulted in record low storage levels. Local fisherman Trent Wilson called the fish kill a "terrible sight and a blow for local businesses." A spokesperson of the water department has assured customers that the local drinking water is as safe as it has ever been.

Memory Questions

NR1—Airplane landing.

F1. What airport did the airplane land at? (a. Kansas City; b. Denver; c. Washington D.C.; d. Seattle).

F2. How many passengers were on board? (a. 100; b. 150; c. 350; d. 500).

F3. What type of aircraft was involved? (a. Boeing 747; b. Airbus A380; c. Boeing 787; d. Airbus A319).

R1—Bushfire.

F1. Where did the bushfire occur? (a. Shepparton, b. Euroa, c. Benalla, d. Kyneton).

F2. What was local resident Casey relieved about? (a. That no one had been harmed; b. That her house had not been affected; c. That her pets had survived; d. That rain had set in).

F3. How many hectares of bushland were burnt? (a. 100,000; b. 25,000; c. 200,000; d. 50,000).

NR2—Death of a drug dealer.

F1. What was the nickname of the drug dealer? (a. Priest; b. Shrink; c. Grandpa; d. Coach).

F2. Who discovered the body? (a. Family; b. Police; c. Neighbour; d. Postman).

F3. What kind of drug did police find on the property? (a. LSD; b. Methamphetamine; c. Crack; d. Ecstasy).

R2—Nightclub.

F1. What nightclub was the woman partying at? (a. Loft; b. Fabric; c. Cable; d. Cargo).

F2. In what city did the incident occur? (a. London; b. Melbourne; c. New York; d. Munich).

F3. Where did the woman study? (a. art academy; b. dance academy; c. science academy; d. fashion academy).

NR3—Train derailment.

F1. Near what town did the derailment happen? (a. Metz; b. Nancy; c. Strasbourg; d. Reims).

F2. What was the death toll? (a. 29; b. 19; c. 3; d. 100).

F3. What did the company of the killed CEO manufacture? (a. tools; b. cars; c. electronics; d. food).

R3—Fish kill.

F1. What water department was involved? (a. Greenacre; b. Wentworth; c. Patterson; d. Freemont).

F2. What is the name of the river that the water supply comes from? (a. Harding; b. Denroy; c. Frederick; d. Morgan).

F3. How many days was intake from the water supply shut down for? (a. 1; b. 9; c. 5; d. 17).

Inference Questions

NR1—Airplane landing.

I1. When planning flight routes, more attention should be paid to weather forecasts. (0-10 scale from "Completely disagree" to "Completely agree")

I2. U.S. guidelines for flying in bad weather should be reviewed.

I3. Bad weather contributed to the emergency landing.

I4. It should be investigated which plane control systems were affected by the weather.

I5. What do you think was the main cause of the incident? (a. Bad weather; b. Lack of servicing; c. Foul play; d. Pilot error).

R1—Bushfire.

I1. Local residents need to look out for suspicious behaviour.

I2. There should be a call for local authorities to spend more resources to prevent arson.

I3. Malicious intent contributed to the fire.

I4. The person responsible for the bushfire should be identified and punished.

I5. What do you think was the main cause of the fire? (a. Accident; b. Extreme heat; c. Arson; d. Lightning).

NR2—Death of a drug dealer.

I1. The family of the drug dealer is likely to seek revenge.

I2. Police should investigate the circumstances of the drug dealer's death.

I3. It would be appropriate for someone to be jailed as a result of the drug dealer's death.

I4. The person responsible for the death should be identified and punished.

I5. What do you think was the cause of death? (a. Heart attack; b. Suicide; c. Assault; d. Accident).

R2—Nightclub.

I1. The affected nightclub should immediately introduce a 'bottled drinks only' policy.

I2. Police should investigate the circumstances of the woman's collapse.

I3. A criminal act occurred at the nightclub.

I4. The person responsible for the incident should be identified and punished.

I5. What do you think was the cause of the woman's collapse? (a. Dehydration; b. Drink spiking; c. Alcohol; d. A medical condition).

NR3—Train derailment.

I1. The driver of the train should be charged with misconduct.

I2. The French Railway (SNCF) should investigate the driver's training and conduct history.

I3. Negligence contributed to the derailment.

I4. An automatic speed-limiting system on the train would have prevented the accident.

I5. What do you think was the cause of the derailment? (a. Collision; b. Mechanical failure; c. Tampering with the track; d. Speeding).

R3—Fish kill.

I1. The riverside pharmaceutical company should start an internal investigation and review their procedures.

I2. Environmental control measures in riverside industrial areas in Missouri should be tightened.

I3. Chemical contamination contributed to the incident.

I4. The riverside pharmaceutical company should be fined.

I5. What do you think was the cause of the fish deaths? (a. Chemical spill; b. Water temperature; c. Virus; d. Algae bloom).

Single-indicator Model

The data were also modelled using the single-indicator approach as per Brydges et al. (2018). The model was found to be associated with excellent model fit, $\chi^2(62) = 78.691$, $p = .075$, CFI = .975, TLI = .969, SRMR = .048, RMSEA = .030 (90% CI [.000, .048]), BIC = 244.864. As can be seen in Figure S3, both WMC (ß = -.02, 95% CI [-.17, .14], $p = .840$) and removal (ß = .07 [-.14, .26], $p = .442$) were associated with non-significant standardized beta weights. By contrast, content span was associated with a significant standardized beta weight, ß = -.62 [-.80, -.41], $p = .007$. As to-be-expected, the WMC and removal latent variable correlation was virtually identical to the two-factor model, and estimated at $r = -.15$ [-.30, .00], $p = .042$. The squared multiple correlation for CIE was estimated as $R^2 = .388$ [.16, .62], $p = .005$. Thus, 38% of the true score variance in CIE was accounted for by the model that included WMC, removal, and content span as predictors of CIE.

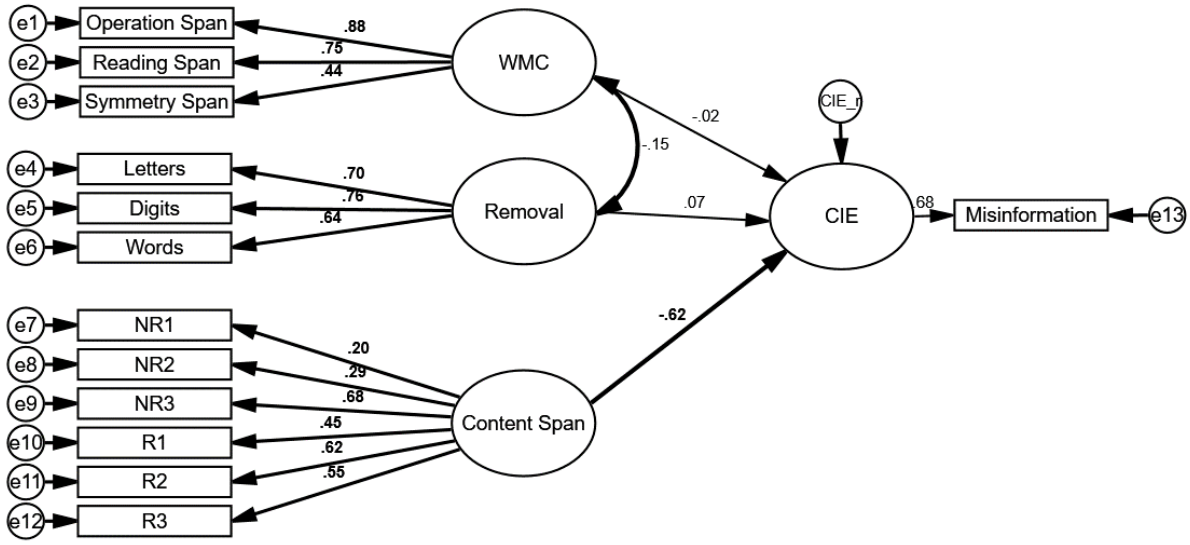

Figure S3. Structural equation model of working memory capacity (WMC), working memory removal (Removal), and content span predicting the continued influence effect (CIE). Straight lines with single arrows are regression paths. Curved lines with double arrows are correlations. Emboldened lines and values indicate statistically significant regression/correlation coefficients ($p < .05$). e1-13 = error variables. CIE_r = residual error associated with the CIE latent variable; coefficients in bold were significant statistically ($p <$ .05).

Alternative Model

We acknowledge that alternative ways of modelling the data exist. Specifically, modelling a CIE latent variable based on a difference score between retraction and non-retraction conditions is not the only way to model continued influence. Further latent-variable analyses were therefore conducted with separate retraction and no-retraction latent variables. To this end, inference scores were calculated separately for each report; with the three average retraction inference scores representing a retraction-inference (RI) latent variable capturing reliance on retracted misinformation, and an additional no-retraction-inference (NRI) latent variable based on the three average no-retraction inference scores. This alternative model with WMC, removal, content span, and NRI as predictors of RI was found to be associated with good model fit, $\chi^2(129) = 138.720$, $p = .264$, CFI = .987, TLI = .985, SRMR = .047, RMSEA = .016 (90% CI [.000, .033]), BIC = 379.384. As can be seen in

Figure S4, the results of this analysis were similar to the original results: the content span regression weight was significant (ß = -.65 [-1.58, -.40], *p* = .017), whereas the WMC (ß = -.06 [-.23, .10], *p* = .427) and removal (ß = .04 [- .14, .21], *p* = .590) regression weights were not. The no-retraction inference variable was also associated with a non-significant standardized beta weight, ß = .64 [.25, 1.72], *p* = .066. The WMC-removal correlation (*r* = -.15 [-.30, -.01], *p* = .043) remained significant, while the content span-NRI correlation (*r* = .33 [.05, .67], *p* = .117) was non-significant. The model yielded R^2 = .558 [.20, 1.69], *p* = .001. Thus, 55% of the true score variance in reliance on retracted information was accounted by the model that included WMC, removal, NRI, and content span as predictors of RI.[7]

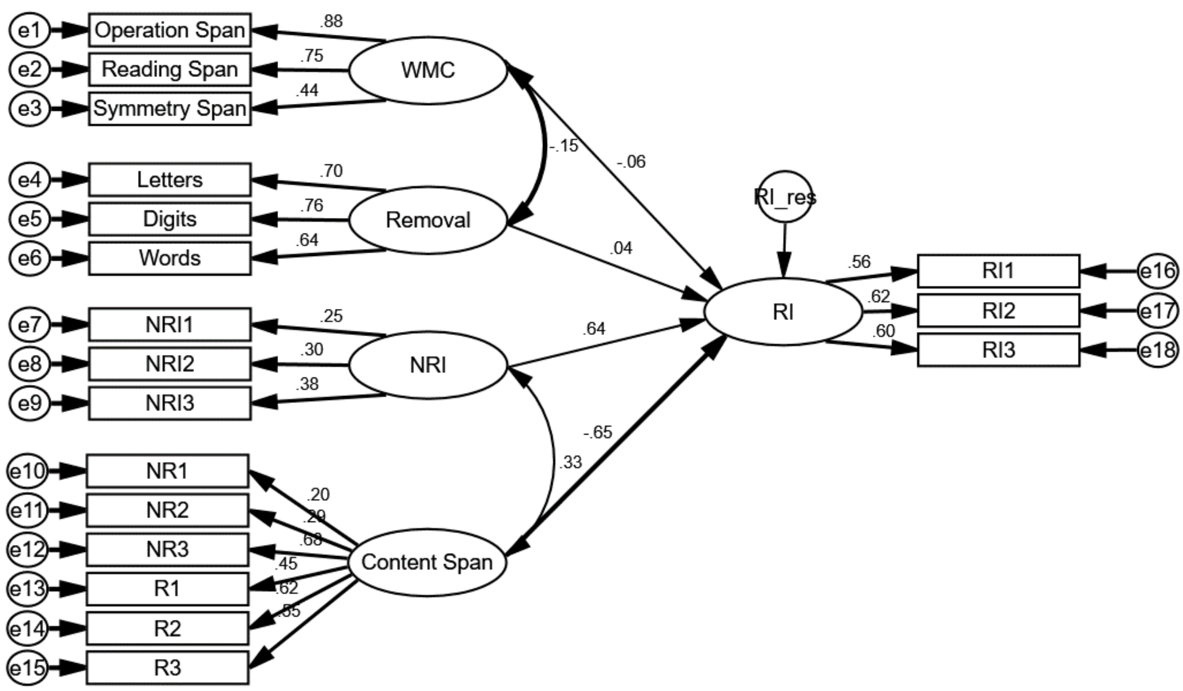

Figure S4. Structural equation model of working memory capacity (WMC), working memory removal (removal), content span, and no-retraction inference (NRI) predicting reliance on retracted information (RI) represented by retraction inference averages. Straight lines with single arrows are regression paths. Curved lines with double arrows are correlations. Emboldened lines and values indicate statistically significant regression/correlation

[7] Although content span was a significant predictor of RI while NRI was not, we note that the effect sizes were roughly comparable in size, and therefore further research is needed to further disambiguate the relative influences of NRI and content span.

coefficients ($p < .05$). e1-18 = error variables. RI_r = residual error associated with the reliance-on-retracted-information latent variable; coefficients in bold were statistically significant ($p < .05$).

Additional Analyses

The data were also modelled with a more lenient cut-off criterion for the misinformation task memory questions to include participants who scored ≥ 6/18. Based on the a-priori exclusion criteria: Participants were removed if (1) they scored below 70% correct on any secondary task in the WM capacity tasks (n = 18) or failed to correctly answer ≥ 6/18 memory questions in the misinformation task (n = 2); and (2) their recall performance in any WM updating task fell 3SDs above or below the condition-wise grand average were (n = 15). Additionally, three multivariate outliers were removed. This resulted in an additional n = 55 participants, thus the final sample was N = 363. Results were comparable to the current study's earlier models.

Preferred model. The first model was found to be associated with excellent model fit, $\chi^2(86) = 106.243$, $p = .069$, CFI = .977, TLI = .972, SRMR = .051, RMSEA = .025 (90% CI [.000, .040]), BIC = 306.653. As can be seen in Figure S5, both WMC (ß = -.04 [-.19, .10], $p = .629$) and removal (ß = .08 [-.12, .27], $p = .359$) were associated with non-significant standardized beta weights. By contrast, content span was associated with a significant standardized beta weight, ß = -.68 [-.86, -.52], $p = .003$. The WMC and removal latent variable correlation was estimated at $r = -.15$ [-.27, -.02], $p = .032$. The squared multiple correlation for CIE was estimated as $R^2 = .469$ [.26, .73], $p = .002$. Thus, 46% of the true score variance in CIE was accounted for by the model that included WMC, removal, and content span as predictors of CIE.

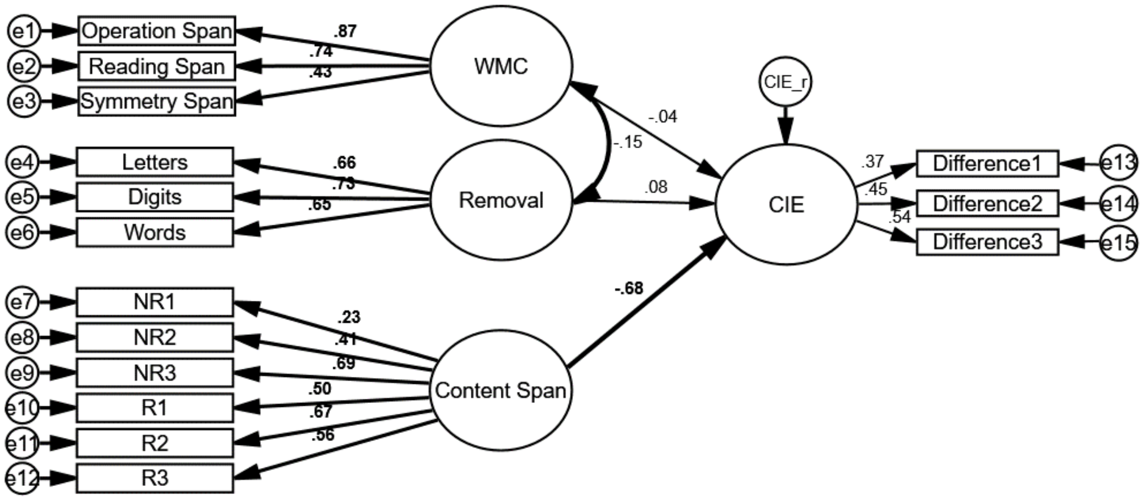

Figure S5. Structural equation model of working memory capacity (WMC), working memory removal (Removal), and content span predicting the continued influence effect (CIE). Straight lines with single arrows are regression paths. Curved lines with double arrows are correlations. Emboldened lines and values indicate statistically significant regression/correlation coefficients ($p < .05$). e1-13 = error variables. CIE_r = residual error associated with the CIE latent variable; coefficients in bold were statistically significant ($p < .05$).

Alternative model. The alternative model was also applied, as seen in Figure S6. The model was found to be associated with good model fit, $\chi^2(129) = 153.316$, $p = .071$, CFI = .975, TLI = .970, SRMR = .050, RMSEA = .023 (90% CI [.000, .036]), BIC = 400.881. The results of this analysis were similar to the original results: the content span regression weight was significant (ß = -.70 [-1.36, -.49], $p = .003$), whereas the WMC (ß = -.06 [-.21, .08], $p = .382$) and removal (ß = .06 [-.11, .21], $p = .447$) regression weights were not. The no-retraction inference variable was also associated with a significant standardized beta weight, ß = .68 [.31, 1.39], $p = .036$. The WMC-removal correlation ($r = -.15$ [-.27, -.02], $p = .033$) remained significant, while the content span-NRI correlation ($r = .34$ [.13, .63], $p = .067$) was non-significant. The model yielded $R^2 = .630$ [.29, 1.54], $p = .001$. Thus, 63% of the true score variance in reliance on retracted information was accounted by the model that included WMC, removal, NRI, and content span as predictors of RI.

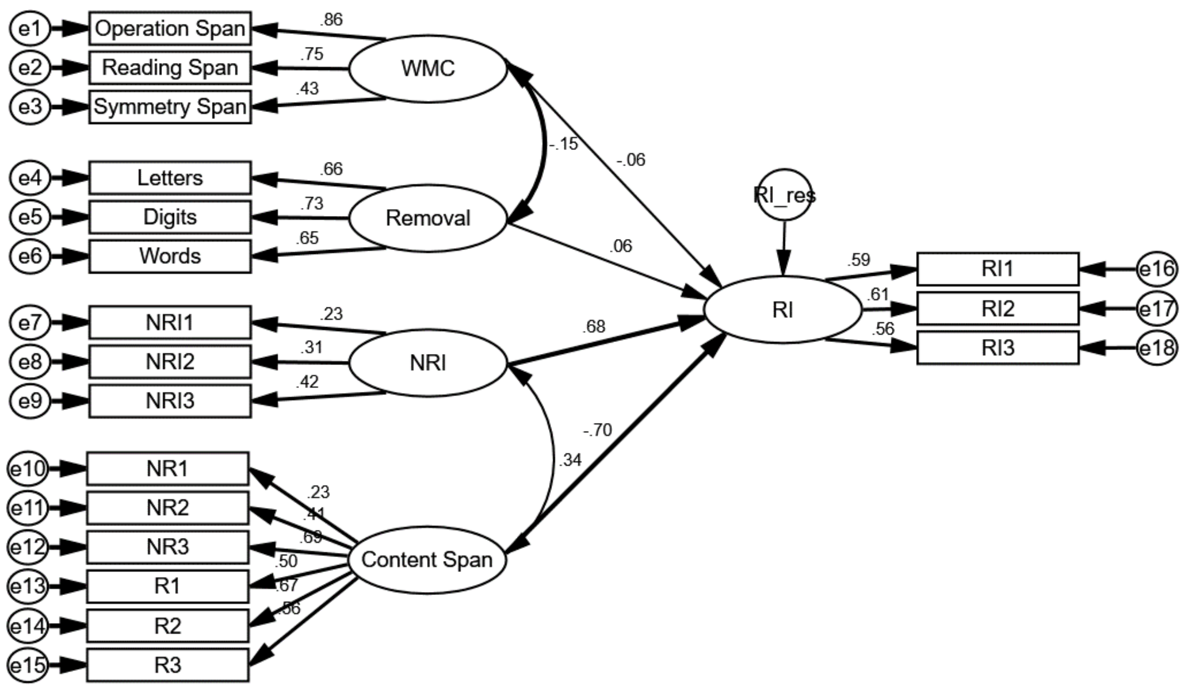

Figure S6. Structural equation model of working memory capacity (WMC), working memory removal (removal), content span, and no-retraction inference (NRI) predicting reliance on retracted information (RI) represented by retraction inference averages. Straight lines with single arrows are regression paths. Curved lines with double arrows are correlations. Emboldened lines and values indicate statistically significant regression/correlation coefficients ($p < .05$). e1-18 = error variables. RI_r = residual error associated with the reliance-on-retracted-information latent variable; coefficients in bold were statistically significant ($p < .05$).

Re-analysis of Brydges et al. (2018) Data—Alternative Model

The alternative model was also applied to the Brydges et al. (2018) data, as seen in Figure S7. The model was found to be associated with acceptable model fit, $\chi^2(128) = 169.287$, $p = .009$, CFI = .936, TLI = .924, SRMR = .080, RMSEA = .039 (90% CI [.020, .054]), BIC = 400.424, thus providing further support for the preferred model. The results of this analysis were similar to the first model: the content span regression weight was significant (ß = -.29 [-.56; -.06], $p = .017$) but the WMC (ß = -.20 [-.51, .08], $p = .181$) and STMC (ß = .16 [-.12, .47], $p = .263$) regression weights were not. The no-retraction inference (NRI) variable was associated with a significant standardized beta weight, ß = .68

[.45, .93], $p < .001$. The WMC-STMC correlation ($r = .70$ [.56, .83], $p < .001$) was significant; however, the correlation between content span and NRI ($r = .23$ [-.01, .47], $p = .055$) was non-significant. The model yielded $R^2 = .479$ [.20, .77], $p = .003$. Thus, 47% of the true score variance in reliance on retracted information was accounted by the model that included WMC, STM, NRI, and content span as predictors of RI.

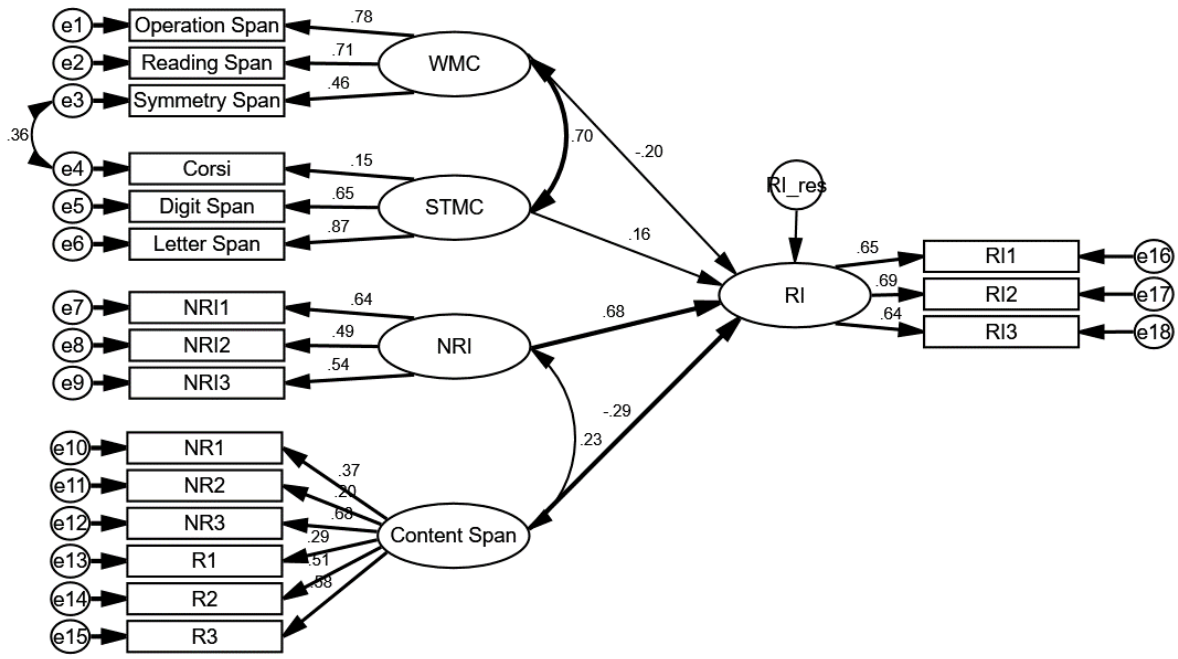

Figure S7. Structural equation model of working memory capacity (WMC), short term memory capacity (STMC), memory for details of the reports (content span), and no-retraction inference averages (NRI) predicting reliance on retracted information (RI) represented by retraction inference averages. Straight lines with single arrows are regression paths. Curved lines with double arrows are correlations. Emboldened lines and values indicate statistically significant regression/correlation coefficients ($p < .05$). e1-18 = error variables. RI_r = residual error associated with the reliance-on-retracted-information latent variable; coefficients in bold were statistically significant ($p < .05$).

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