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Working memory capacity mediates the relationship between removal and fluid intelligence

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ABSTRACT

A process of active, item-wise removal of information from working memory (WM) has been proposed as the core component process of WM updating. Consequently, we investigated the associations between removal efficiency, WM capacity, and fluid intelligence (gF) in a series of three individual-differences studies via confirmatory factor analysis. In each study, participants completed a novel WM updating task battery designed to measure removal efficiency. In Study 1, participants additionally completed a WM capacity task battery. In Study 2, participants completed a battery of well-established measures of gF in addition to the updating battery. In Study 3, participants completed the updating, WM capacity, and gF task batteries. The results suggested that removal efficiency was related to both WM capacity and gF. Furthermore, based on a mediation analysis, the relationship between removal efficiency and gF was found to be entirely indirect via removal's influence on WM capacity. The results were interpreted to suggest that removal ability may contribute to performance in reasoning tasks effectively through increasing WM capacity, presumably through reducing interference from distracting information.

Introduction

Working memory (WM) is a capacity-limited system responsible for the temporary maintenance and manipulation of a select set of representations for ongoing cognition (Baddeley, 2000; Miyake & Shah, 1999; Oberauer, 2009). Traditionally, research has focused on the storage capacity of WM. However, some have argued that the main purpose of a WM system is to serve higher-level cognition (Oberauer, 2009). Indeed, WM capacity is one of the best known predictors of reading comprehension (Daneman & Merikle, 1996), reasoning ability (Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002), and general intelligence (Conway, Kane, & Engle, 2003).

Serving higher-level cognition in an environment that constantly changes, however, poses a conundrum for WM: the system needs to construct representations that are both stable—a purpose of any memory system—and flexible at the same time. In other words, contents of WM need to be protected from forgetting and interference, while the system needs to be able to flexibly replace subsets of information in order to meet varying processing requirements. Recent evidence points to the idea that these dual goals are achieved by switching between maintenance and updating modes of operation (Kessler & Oberauer, 2014; also see Artuso & Palladino, 2011; Ecker, Oberauer, & Lewandowsky, 2014; Murty et al., 2011; Roth, Serences, & Courtney, 2006). The exact processing mechanisms underlying maintenance and updating, however, are still under debate.

Regarding maintenance, there are differing perspectives regarding the nature of WM's capacity limitation. Two of these perspectives include the decay theory and the interference theory. The former proposes that forgetting is exclusively a function of time, because memory traces decay passively (e.g., Baddeley, 2000; Barrouillet, Bernardin, Portrat, Vergauwe, & Camos, 2007; Barrouillet, De Paepe, & Langerock, 2012). This necessitates a process of attentional refreshing or sub-vocal rehearsal to counteract decay and keep selected items available for ongoing processing (Baddeley, 1986; Camos, 2015; Vergauwe & Langerock, 2017). Rehearsal, however, can only keep a certain number of representations active in the face of decay. This may be considered an intuitive explanation of the capacity limitation of WM. However, it has been largely rejected, at least in the verbal WM domain, based on an accumulation of evidence that the mere passage of time does not cause forgetting (e.g., Berman, Jonides, & Lewis, 2009; Farrell et al., 2016; Lewandowsky & Oberauer, 2015; Lewandowsky, Oberauer, & Brown, 2009; Nairne, 2002; Oberauer, Farrell, Jarrold, & Lewandowsky, 2016; Oberauer & Lewandowsky, 2008, 2013; Souza & Oberauer, 2015).

By contrast, the latter view argues that interference between representations is the primary limiting factor of WM. According to this

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perspective, the processing of events, as and when they occur, interferes with our ability to retrieve information (Ecker & Lewandowsky, 2012; Kane & Engle, 2000; Lewandowsky, Geiger, & Oberauer, 2008; Lustig, May, & Hasher, 2001; May, Hasher, & Kane, 1999; Oberauer & Kliegl, 2006). Interference-based models thus view forgetting as a result of distracting information creating interference by being encoded into WM. There are both theoretical and empirical reasons to accept this. First, computational models of WM can account for a large body of data based on interference mechanisms without decay (e.g., Farrell & Lewandowsky, 2002; Oberauer & Lin, 2017). Second, studies show that interference influences performance on complex-span tasks.[1] For example, Lewandowsky et al. (2008) conducted a study where participants studied lists of five consonants for serial recall. The interval between memoranda was held constant, but the number of distractor words presented in-between list items was manipulated. Moreover, in one condition, distractors were unique (i.e., consecutive months such as "January", "February", "March"), whereas in another condition distractors were repeated (e.g., "January", "January", "January"). Results showed that a greater number of distractors caused more forgetting in the unique-distractors condition but not the repeated-distractors condition, arguably because with unique distractors, interference increased with the number of distractors. Comparatively, with repeated distractors, participants were faced with interference from only one distractor word, not multiple. In other words, forgetting was a function of the amount of distracting information processed in a given interval of time, rather than a function of the time interval's duration itself. It follows that—to avoid interference-based forgetting in the absence of time-based decay—WM requires a mechanism to remove out-dated or distracting information.

With respect to updating, previous research has identified the substitution of information as the core process involved in WM updating (Ecker, Lewandowsky, Oberauer, & Chee, 2010). The substitution process itself can be subdivided into two component processes: (1) outdated, irrelevant information needs to be removed, and (2) newer, more relevant information needs to be encoded. Thus, the requirement of a removal mechanism follows not only from WM's capacity limitations, but also from a decomposition of the WM updating process. In other words, the implication of a WM system that has limited capacity and requires representational flexibility is that there needs to be a process that 'clears' WM of information that is or has become irrelevant.

Therefore, it has recently been proposed that an active removal process exists, serving (a) to minimize interference (and thus forgetting) in WM, and (b) to facilitate the updating of information held in WM. In the domain of WM capacity, active item removal has been incorporated successfully into a computational model of WM as a Hebbian antilearning process, in order to model the reduction of distractor interference in the complex-span task (Oberauer, Lewandowsky, Farrell, Jarrold, & Greaves, 2012). In the domain of WM updating, Ecker, Lewandowsky, and Oberauer (2014), Ecker, Oberauer, et al. (2014) have provided experimental evidence for the importance of active item removal in WM updating. They correspondingly introduced a novel WM updating task that serves to measure reliably a person's removal efficiency. A brief discussion of this removal process, and the evidence supporting it, follows.

A measure of removal efficiency

A disadvantage of using traditional updating tasks to measure WM updating is that they confound updating with generic WM processes. Tasks such as the running memory task (Morris & Jones, 1990) and the *n*-back task (Kirchner, 1958) require participants to maintain information in WM, while substituting outdated items with newer ones—therefore, while they do measure WM updating, they also measure generic processes such as encoding, maintenance, and retrieval. In fact, it has been argued that traditional updating tasks measure WM capacity equally as well as complex span tasks (Schmiedek, Hildebrandt, Lovdén, Wilhelm, & Lindenberger, 2009). For example, in the running memory task, participants encode an item list of unpredictable length (e.g., K, A, S, G, F, V), before recalling the last 3 letters presented when prompted. Successful updating would imply that, over time, participants represent this list in WM as "K…KA…KAS…ASG…SGF…GFV" and that they recall "GFV" at the end of the trial. Even though one could argue that individual items of a set need to be repeatedly updated in this task, the task just measures final recall of the set and, thus, conflates updating, maintenance, and retrieval processes. In addition, it is possible that people who successfully recall the final set in this task do not actively engage in WM updating throughout the trial, but instead base their recall on item recency alone (Bunting, Cowan, & Saults, 2006).

To measure updating more directly, Kessler and Meiran (2008) measured the time it took people to replace items held in WM. Participants encoded a set of three items, and individual items were repeatedly replaced with new ones before a final recall. At each updating step, participants pressed a key when they had completed the updating, providing a measure of updating efficiency. However, because participants in Kessler and Meiran's task did not know what item was going to be replaced, Ecker, Lewandowsky, et al. (2014) argued that this measure still confounded the core updating process of removal with the generic operations of attention reorienting and encoding, as all three processes could only begin when the new item was presented.

To disentangle the removal and encoding confound, Ecker, Lewandowsky, et al. (2014), Ecker, Oberauer, et al. (2014) varied Kessler and Meiran's (2008) task in two ways. First, they cued the to-be-updated item. Providing a cue gave participants information on what needed to be removed, thus, facilitating the updating process. Specifically, at each updating step, the cue signalled to participants what item was about to be updated, prior to the presentation of the new to-be-encoded item. It was assumed that people could use the time between the presentation of the cue and the presentation of the new to-be-encoded item (i.e., the cue-target interval, CTI) to remove the out-dated representation from their WM.

Secondly, Ecker et al. varied the CTI, thereby manipulating the time available for item removal: It was assumed that a short CTI (i.e., 200 ms) did not permit any removal because it only allowed sufficient time to focus attention on the to-be-updated item; updating response latencies in this condition were thus assumed to include both the time required to remove the old item and the time required to encode the new item. By contrast, a long CTI (i.e., 1500 ms) was assumed to allow for removal of the cued item prior to the presentation of the new item; updating RTs in this condition should thus not include the time taken for removal.

As expected, updating latencies in Ecker, Lewandowsky, et al. (2014), Ecker, Oberauer, et al. (2014) were considerably faster in the long-CTI condition than the short-CTI condition. In addition, it was found that a speed-up of updating observed in previous research (a) when the new item matches the old to-be-replaced item (i.e., occasional item repetition; cf. Ecker et al., 2010) or (b) when the new item is similar to the old to-be-replaced item (i.e., item similarity; cf. Lendínez, Pelegrina, & Lechuga, 2011) was evident in the short-CTI condition but much diminished in the long-CTI condition. These results indicated that representational overlap associated with item repetition/similarity can only facilitate updating to the degree that the to-be-replaced item is still in WM, and thus supported the removal notion (for a more detailed discussion of the removal-efficiency measure's validity, see Ecker, Lewandowsky, et al., 2014; Ecker, Oberauer, et al., 2014).

Ecker, Lewandowsky, et al. (2014), Ecker, Oberauer, et al. (2014)

[1] The complex-span paradigm is the most prominent experimental paradigm used to measure WM capacity; it involves both maintenance and manipulation aspects, requiring maintenance of a list of memoranda (e.g., a set of letters or words) for immediate serial recall while undertaking a distracting processing task (e.g., mental arithmetic) concurrently (cf. Conway et al., 2005; Wilhelm, Hildebrandt, & Oberauer, 2013).