The Role of Individual Storage Strategies in Describing Visual Working Memory Capacity

An account for incorporating individual encoding strategies in the models that describe visual working memory capacity.

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Abstract

Visual working memory is the cognitive system that temporarily stores visual information that can quickly be accessed to serve the needs of an ongoing task and it is essential for many other cognitive activities. How much information we can actively hold in mind is severely limited and why some have greater capacity than others is highly debated. Capacity varies substantially between individuals, which is partially due to the use of different storage strategies. A debate has arisen whether visual working memory capacity can best be described as a discrete limit or a continuous resource. Although studies emphasise the individual differences in performance, the models that try to describe visual working memory capacity have not incorporated leeway to account for the strategies. Here, a literature review about the two dominant models for VWM capacity is presented followed by an overview of arguments that highlight different strategies. Given the theoretical background, the discussion describes how the strategies can fit into the discrete and continuous models and moves towards a conclusion about the role of strategies in describing VWM capacity. The results of the current study provide support for taking into account the encoding strategies of individuals when constructing and analysing VWM capacity models.

Keywords: visual working memory, capacity, strategies, discrete, continuous

Contents

1. Introduction

1.1 Visual Working Memory

Every day our brain has to process an overwhelming amount of visual information. To understand all this information we have to use our memory system to store representations in mind for later use. The visual working memory system is the cognitive system that temporarily stores visual information that can quickly be accessed to serve the needs of an ongoing task. Working memory (WM) in general is crucial in everyday functioning, since it is essential for many cognitive activities like reasoning and decision making. How much information we can actively hold in mind is severely limited and why some have greater capacity than others is highly debated. In literature there is little consensus among researchers whether VWM capacity can best be described as a discrete limit or a continuous resource. *Discrete models* propose that only a number of fixed items can be stored in memory. No information will be retained for further items. Contrary, *continuous models* suggest an infinitely divisible resource among all items, but with fewer resources per item and therefore less precision (Luck & Vogel, 2013). However, studies show that VWM capacity varies substantially across individuals. For instance, participants show differences in attentional processing and individuals use different neural areas to create and retain information in mind, which indicates different cognitive strategies (Pearson & Keogh, 2019). Despite those differences, the models describe a one-way capacity storage and do not incorporate the different cognitive strategies that people use when performing a VWM task.

1.2 Relevance

Alan Baddeley's multi-component model of memory introduced the concept working memory in a way that its role was not just to store only simple, temporary information. Instead, he came up with the idea that WM is a system that provides the basis for other complex cognitive abilities like learning and reasoning (Baddeley, 2010). Furthermore, authors suggested that working memory is related to *fluid intelligence*, which refers to the ability to reason and solve new problems, independently of previously acquired knowledge (Fukuda et al., 2010; Jaeggi et al., 2008). In addition, several studies are optimistic regarding the value of training working memory as a tool for general cognitive enhancement (Morrison & Chein, 2011). Thus, understanding the capacity of visual working memory, could provide important comprehension into overall cognitive functioning. Subsequently, cognitive theories and models can give insight into the complex human thinking process with making predictions about tasks and performance and thus helps to understand human information processing. Those cognitive models are used to create Artificial Intelligence (AI) systems. An AI device must know how to interpret environmental information, just like how humans have to interpret the environment through their sensory organs. The goal of AI is to create a system which is able to produce a form of intelligence. Cognitive models are used to help implement intelligence in an AI system. Therefore, with the aid of knowledge about human visual working memory and the underlying cognitive processes, cognitive models can be build which can help to create the ultimate goal of AI.

1.3 Method

In the current study, the following question is addressed: *What role do individual differences in storage strategies play in the way visual working memory capacity is best described?* In this review, the two current prominent models are examined from a new perspective which indicates a direction towards further research in the field. First, the discrete and flexible frameworks are discussed and previous research is synthesized. Then, an overview is presented with arguments that explain that individuals use different storage strategies while performing a VWM task. Finally, the findings are discussed by investigating how the models incorporate different individual strategies. Based on the findings the conclusion will be a statement about how the individual strategies are incorporated in the models and emphasises the need for a shift in the debate towards a more well-founded, strategy-driven discussion.

2. Theoretical background

2.1 Visual Working Memory Capacity

Working memory is typically described as the cognitive ability to hold and manipulate a small amount of information temporarily. Since the term working memory evolved from Baddeley's memory model, its active role has gained attention in literature for decades and the concept of working memory has come to play a substantial role in theories of cognition.

Visual Working Memory (VWM) is the part of working memory that is responsible for retaining visual information relevant for an ongoing task (Luck & Vogel, 2013). One aspect of visual working memory that has been considerably scrutinized, is its capacity. The capacity of VWM refers to the ability to store visual information. A significant part of the VWM debate focuses on how VWM capacity can best be described. Two classes of theories are primarily highlighted: the *discrete*[1] and *continuous* models[2]. The discrete models presuppose that only a certain amount of items can be stored in memory. No information will be retained for further items. Although still debated, an item limit from 3 to 5 representations seems to be considered as the maximum capacity (Cowan, 2001; Luck & Vogel, 2013). In contrast, the continuous models suggest that there is an infinitely divisible resource among all items, but with fewer resources per item and therefore less precision. In this view, there is no upper limit for the amount of representations in mind.

One common way to make a distinction between the two models is to investigate whether VWM becomes less precise when the set size increases. When the number of presented stimuli exceeds the capacity limit, the accuracy of a participant should decrease, as predicted by resource models. A discrete theory would assert all-or-nothing encoding where additional

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[1] Also referred to as *slot models.*

[2] Also referred to as *flexible models* or *resource models*.

items would not be remembered and hence reflect a guessing strategy. The prominent measurements used to asses visual working memory fall into a short-term recall paradigm. One of those recurrent tasks is the *colour wheel* task (Figure 1). Here, a set of coloured squares is shown for a brief period of time and the participant is asked to hold the colours in mind. After a short delay period, the colour wheel is shown with a cued sampled item and the participant is asked to select the colour of the item that was presented at that location. If the probed item is successfully stored in memory, the given response will be near to the original colour on the wheel. When the item has not been stored, a participant will have no information about the colour and therefore the response would be random. With this measurement, Zhang and Luck (2008) found that observers can remember a small number of items with high-resolution, with no information for additional representations, indicating a discrete capacity. However, using the same paradigm, contradicting findings emerged. Bays et al. (2009) concluded that the results could be explained by a resource model which they clarified with two main arguments: Zhang and Luck found high frequency guessing and indicated an upper limit storage capacity. However, Bays et al. argue that the memory array was shown too shortly to encode the items and second, the orientation feature of the stimuli was overlooked, just focusing on colour and therefore, those errors were not accounted for. This would explain the high frequency of guessing. Furthermore, the power law that Bays et al. presented, showed a decrease of precision already from one to two items, which is inconsistent with a fixed-slot model. This contradiction, same task, different interpretation of results, illustrates an example of the complexity of the debate.

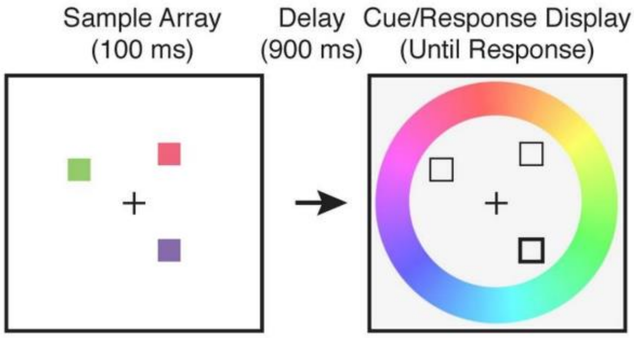

Figure 1. Colour wheel task. A sample of coloured squares is shown, followed by a delay interval. The second display presents a continuous colour wheel and a probed item. Here, the probed square is at the location of the purple square, so observers should click around purple on the wheel (Luck & Vogel, 2013).

Another widely used measurement in memory research is change detection. In a change detection task, subjects have to report whether a difference occurred between two scenes separated in time. Keshvari et al. (2013) used a change detection paradigm on orientation to provide evidence in favour of continuous models (Figure 2). The study compared three item-limit models and two continuous resources models. It was found that the human change detection performance was best explained with a variable precision (VP) model, since encoding precision was variable across items and trials. The VP model is a continuous model, which allows variability in precision across items. Furthermore, a study was conducted wherein participants had to report 6 (out of 8) memorized colours and the total amount of correct responses for each trial was plotted as their score. This distribution of scores was clearly a better fit with the resource model and inconsistent with the slot model (Huang, 2010). In addition, Ma et al. (2014) reviewed the VWM capacity debate and concluded from combined previous studies that when the number of to-be-remembered items increases, precision of recall decreases continuously. These findings are in line with a continuous model since in a discrete model items would be remembered with high precision or not at all.

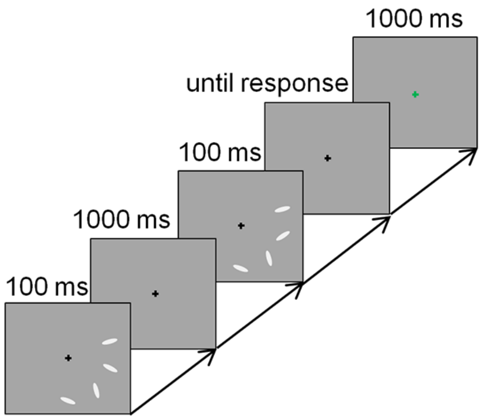

Figure 2. Change detection task on orientation. Observers report whether a change occurred in the orientation of the lines (Keshvari et al., 2013).

Contrary to the abovementioned support for continuous models, more evidence in favour of the discrete capacity approach is presented by Alvarez and Cavanagh (2004). Their experiment showed that only 4 or 5 items can fit in storage capacity, but this varies between different types of stimuli (e.g. coloured squares versus Chinese characters). They note that this variation contradicts every VWM model which states capacity limit is only fixed on a maximum number of items, since capacity also depends on the total visual information load. However, the overall limitation of 4 to 5 items cannot be exceeded for any type of stimulus, which indicates a discrete limitation theory. Although also favouring discrete models, it was later found that VWM represents a fixed number of items regardless of their complexity (Awh et al., 2007). This contradicts the earlier findings of 2004 which showed a variation in item limit for more complex stimuli. The set of chosen stimuli in a task influences how the results are interpreted and therefore the type of stimuli should be incorporated in the conversation about VWM capacity.

To distinguish between discrete and continuous models, recently Pratte et al. (2017) presented a study which evaluated and compared a discrete capacity model and the variable precision model. When applied to errors independent of the type of stimulus, the VP model outperformed the discrete model. However, their results showed that performance was consistent with stimulus specific factors which had a strong influence on VWM. Once this systematic variability was included in both models (instead of random variability) the discrete capacity limit provided a better account for explaining the pattern of VWM errors.

Additional evidence favouring a discrete limit has been found with the use of neurological findings. So far, the discussed findings were primarily based on behavioural tasks while lately there has been growing use of neurological measures to contribute to the VWM capacity debate. Predominantly the *Contralateral Delay Activity* (CDA), a brain activity signal, is used to investigate VWM load. In neurological studies, EEG is used to record brain activity while a subjects performs a task. With sensors attached to the scalp, electrical impulses in the brain are analysed and send to a computer that records the results. With this method, studies observed an Event-Related Potential (ERP) during the delay interval of a VWM task. This signal is called the CDA, a negative amplitude which corresponds to the number of items retained in VWM. When set size increases, this amplitude reaches an asymptote at capacity limit, predominantly 3 to 4 items (Vogel & Machizawa, 2004; Luck & Vogel, 2013). A corresponding effect is also shown in functional magnetic resonance imaging (fMRI) studies, where the signal in the intraparietal sulcus (IPS) reaches an asymptote at the VWM capacity limit of an individual (Luria et al., 2016). In short, neurological measures have found an electrical signal which reflects the number of items that can actively be maintainef in VWM capacity.

Despite the impression the above described studies might give, the dividing line between the two models as explicated above, is not necessarily fixed. This is illustrated by a three factor comparison of working memory models based on all the possible combinations of previous suggested models, with in total a model space containing 32 models. For the factor mnemonic precision, it was found that precision is continuous and variable across items instead of being equal across items, supporting continuous resource models. Regarding the second factor (number of remembered items) the result was inconclusive. Differences were too small for strong claims, but the results do suggest that previous literature has underestimated the number of remembered items, in some models a mean of 6.4 was found, which is much higher than the 3 or 4 items found in basis models. Their mixed conclusion could reflect individual differences like motivation and remembering subsets instead of all the items. Whether incorrect binding of features to location occur, was described as the third factor. Subjects sometimes reported nontarget items but their nature was unclear. If they reflect spatial binding errors, that could be due to positional uncertainty or visual crowding they can be a bottleneck for object recognition. This kind of model ranking highlights the importance of mixing and matching to identify the values that make a model successful and it aims to rule out poorly fitting models (Van den Berg et al., 2014). Furthermore, like the variable precision model, different models are suggested. For instance, the *slots+resources* and the *slots+averaging* model. Slots+resources reflects a maximum number of slots, added with a limited pool of resource, which makes it possible to allocate resources in different quantities to the slots. In the slots+averaging model, multiple slots can be used to store a representation of one object and observers can report the average of those representations (Zhang & Luck, 2008). The model variations in research emphasize that the debate is still open and not fixed to just two models. The discrete versus continuous discourse contains two classes which both can accommodate combinations of models. However, the subject matter of this paper concentrates on the two specified models.

2.2 Individual Storage Strategies

Within de VWM capacity debate, studies have found individual differences in task performance, which can partially be explained by the storage strategies subjects use. The VWM capacity variation across individuals has been described in research but it is unclear whether the different encoding strategies fit the models. The hypothesis that strategies influence visual working memory performance was, among others, confirmed by Bengson & Luck (2016). They found this through an experiment that offered different participants an explicit strategy instruction for a change detection task. By encouraging a more effective strategy an increase in estimated capacity was found. The results of their experiment showed that an instruction to remember all the items (instead of only a subset) yielded the best performance. However, in this study, the display showed unidimensional items. To investigate whether the same outcome was found for more complex items, Atkinson et al. (2018) performed an experiment with items that contained several features like colour, shape and depth, which had to be connected. Since the complexity of the items is higher, it might be harder to encode all the presented visual information, which suggests that "remember-all" would not be the optimal strategy. It was indeed found that focusing on a subset of complex items resulted in better performance compared to trying to remember all the visual information.

Originally, within the VWM capacity debate, the *filter account* refers to an individual's ability to filter distraction. However, with the shift towards flexible distribution of resources within memory, Dube et al. (2017) investigated a more sophisticated role for attention, contrary to simply restricting the encoding of distractors in a display. In general, attention seems to regulate VWM by both filtering and distributing resources to items, in agreement with the goal of the subject. Since attentional processing is strongly related to VWM, attentional filtering is one of the most-studied factors that influences an individual's capacity limit. The interaction between the two cognitive mechanisms has been further explored since the emergence of continuous models. Mayer et al. (2007) used fMRI to test whether capacity constraints are due to the common neural resources that VWM and selective attention share. The authors used a visual search task wherein participants were presented with a search array and asked to memorize only the objects marked with a target item in both easy and difficult conditions. A secondary task was what the authors called a delayed discrimination task, wherein a search array was presented and participants had to report whether a probe consisting of a single object matched one of the memorized objects. It was found that the same brain areas are active when performing these tasks, which indicates that encoding into VWM and visual selective attention require common neural resources. These shared neural correlates can be a cause for the limitation both mechanisms have. Considering further contributions to the VWM and attention discourse, Irons and Leber (2016) conducted an experiment about goal-directed attentional control in visual search and they established that at least two strategies drive simple attentional control: performance maximization and effort minimalization. The former is about optimizing the settings for maximum accuracy or speed and the latter is about selecting the least effortful settings. Besides, they suggest that this is not the complete story and propose that at least one additional factor can drive attentional control. Thus, the contribution of attention in any VWM analysis cannot be neglected, since it has a substantial role in the storage of items in memory.

Another relevant point to address is that studies of attention and capacity often distinguish between high- and low-capacity VWM individuals. The fact that this distinction exists is a strong indicator of individual differences in encoding strategies. Variations in capacity can be predicted with the aforementioned CDA. This neural signal reflects the retainance of active representations in visual memory. A strong correlation is found between an individual’s memory capacity and the increase in amplitude of the CDA signal. Hence, the CDA is a strong neurophysiological predictor of VWM capacity since high-capacity subjects show a larger amplitude increase compared to the low-capacity subjects (Vogel & Machizawa, 2004). Indeed, Gulbinate et al. (2014) revealed that high- and low VWM capacity individuals use distinct strategies to filter out information. Whereas high-capacity individuals show attentional suppressing of the irrelevant stimuli, low-capacity subjects show attentional enhancement of the relevant stimuli. Filtering can be achieved by enhancing the representation of a to-be-remembered item or by suppressing the representation of a to-be-ignored item. It is suggested that the inability to suppress distractors predicts a low-capacity storage. This filtering-efficiency hypothesis proposes that controlling attention can consume memory capacity and in addition it states that low-capacity individuals inefficiently encode information since they store the information of the entire display, including the irrelevant details (Gaspar et al., 2016; Vogel et al., 2005).

An alternative storage strategy has been put forward by Pearson & Keogh (2011; 2014). Asking participants about their approach resulted in the possible strategy of creating a detailed visual mental image in mind. These reports suggest *visual imagery* as a possible cognitive strategy to solve VWM tasks. Binocular rivalry was used to show that performance in visual working memory can be predicted by the strength of mental imagery. With this method, perception is alternated between different images presented to each eye. Modulating the background luminance for individuals with strong mental imagery showed a diminishing performance on visual working memory tasks, but not for number-strings. By disrupting the sensory-based mechanisms the subjects used, a dichotomy in strategies for VWM occurred. Individuals with strong mental imagery rely on sensory-based imagery to support mnemonic performance, while individuals with poor imagery did not show this strategy. Furthermore, visual imagery was tested on an individual with aphantasia, which refers to the inability to generate mental images. For VWM tasks the individual performed worse than controls.

However, a tasks which was designed to involve visual imagery did not differ from controls, although the participant lacked metacognition about her performance. The results indicate that mental imagery has a role in visual working memory and that tasks which involve mental imagery can be performed with another strategy that can result in equally successful behaviour (Jacobs et al., 2018). Hence, forming a detailed, mental image from a display is a possible strategy to deal with a VWM task and since recently discovered, deserves attention in the discussion.

In addition, the use of *chunking* as a strategy in working memory was used to describe a mnemonic strategy. For instance, encoding the separate numbers 2-0-2-1 as a single date (2021) can be stored in memory more effectively. Although the definition of a chuck in the context of visual WM (binding features together to treat them as a complete unit) remains slightly unclear, the use of chunking as a strategy does reduce the load on capacity and therefore leaves more room for additional information (Thalmann et al., 2019). Similar features are jointly encoded through the chunking process to form one object. This is contrary to encoding every single feature of an item. Nassar et al. (2018) show that it is beneficial to encode similar features together and only encode single features if they are sufficiently different. The human visual working memory system can rapidly implement the chunking strategy to improve performance. This work is in line with previous findings that highlight the use of chunking as a mnemonic strategy and in general it seems to be the consensus that grouping features together and integrate them as objects is the predominant behaviour (Vogel & Luck, 1997).

3. Discussion

Previous studies evaluating VWM capacity observed inconsistent results on whether VWM capacity could best be described as a discrete limit or a continuous resource. More recent, the focus has shifted towards not only understanding VWM capacity itself, but to the differences that occur in performance and why they arise. Consequently, different encoding strategies an individual can use while performing a VWM task, are frequently mentioned in the studies. Remarkably little attention is given to how these strategies fit into the model that describes VWM capacity. Although extensive research has been carried out to the subject, it is interesting to look at the role of individual differences in storage strategies and reflect on how they can fit into the predominant models. The section below describes the proportions of the models and the strategies and which corresponding issues are involved.

As previously stated, studies show that individuals are able to choose how they control attention as a specific kind of strategy to use when performing a VWM task. With the use of such a mechanism, the continuous models could probably account best for explaining how storage is structured, since it contains a flexible resource which can be allocated to items. In addition, attention is not only a filter that takes care of whether or not information is stored in memory, but it also regulates the distribution of VWM resources (Dube et al., 2017). For instance, when one wants to remember a certain subset of items, more attention can be assigned to these items and accordingly the resource can be spread among them. As a result, the items that receive the most attention, and thus resources, are stored with the highest precision. The continuous model contains the assumption that there is no upper bound, so remembering a subset of items would not be necessary, since there is actually room for all the items in capacity. However, it might be an efficient strategy to use, since the items which receive the most resources are stored with the highest precision and remembering all the items would reduce precision. In the same way, the notion of variability in performance is best incorporated in the continuous theories. Each individual´s distribution of resource allocation to items can vary substantially, which can account for the differences between subjects. However, it is noteworthy that a flexible resource account does not directly discard the discrete models because it is still possible an upper limit exists. The resources can be divided in different quantities between a maximum amount of items.

Research has only treated chunking as a possible strategy to encode information in WM, but has not dealt with incorporating the strategy into the VWM capacity views. As for the idea of chunking, there seems to be a consensus about storing objects as a combination of integrated features. Rejecting this thought and stating that we encode single features would reject discrete models since traditionally, object-based representations are in favour of the discrete models, since the complete objects fit into one slot. Thus, a discrete approach might be a good fit for explaining a chunking strategy that combines features to form one object. However, the structure of a representation is omitted here, since discrete models do not explain how complex stimuli are represented in memory. Furthermore, chunking happens for similar features, and features that are sufficiently different are encoded separately. So when an item is simple to define, it is easy to say that an object fits a slot. But when single features are bound together, questions arise about how the features are exactly encoded in a discrete fashion. On the other hand, for continuous models the solution is not straightforward either. For instance, do different features like shape and color compete for the same resource pool? And within the flexible models, can resources be dedicated to single features, groups of features or whole objects? The specific extent to which resources can be distributed to stimuli and how objects are represented in memory remains to be seen.

When further discussing the complexity of stimuli, it is noteworthy that VWM capacity is consistently measured by simple visual features. Although for instance polygons and Chinese characters are included in experimentation as ‘complex’ items, an object in a natural real-world scene is difficult to define, contrary to an item in a laboratory setting. In continuous models, resource can possibly be described as being allocated to (groups of) features, objects or spatial locations, rather than to just one item. So within natural scenes, the continuous models have an advantage over discrete models as the definition of an item already captures what information goes into a slot (Ma et al., 2014).

Perhaps one of the most significant issues within the debate, is the fact that research has found an upper limit for items that can simultaneously be represented in WM. This number is generally found with the neurological CDA signal which reflects the amount of items that can actively be retained in memory. This evidence is hard to explain through resource models, since they do not contain an upper bound for the amount of items that can be stored in memory. A suggested view is a two-factor model which accounts for both the number of items and the resolution (precision) an item is stored in (Fukuda et al., 2010). This more nuanced view of visual working memory capacity requires a strategic trade-off between storage capacity and memory precision. Whenever the word trade-off is mentioned in this context, it seems to invalidate discrete models. Nevertheless, although often stated as all-or-nothing encoding, there is some room for flexibility in the discrete models, since it is possible to allocate resources between a maximum number of items. An example taken from Zhang & Luck (2008): when having three cups (slots) and a bottle of juice (resource), it is possible to pour more juice to one of the cups, leaving a few drops for the others, with only the maximum number of three cups available to divide the juice between. This analogy illustrates the slots+resources model and can result in an explanation for the quantity versus quality trade-off. Thus, although the discrete models do not predict a trade-off when item limit is exceeded, it is a false assumption that they have no room for flexibility at all. On the other hand, the continuous model can probably more naturally explain the trade-off, since it allows flexible allocation. However, with a strategic consideration for quantity and precision, a single resource might not be suitable, since it has to be divided between two factors. How would the distribution of resources be managed when it is required to share it between both the number of items and precision for each item? However, in general, any decrease in memory precision when quantity increases, would be consistent with a continuous resource model and therefore, when discussing a two-factor model of VWM capacity, the flexible models are the most suitable, since discrete models have no expanse for a precision factor.

Returning briefly to the visual imagery subject of the previous chapter, the ability to create a mental image in mind was found as a possible approach to memorize items. To establish whether imagery and visual working memory have shared cognitive resources in early visual cortex, Albers et al. (2013) used neural activity patterns to find possible similarity between neural representations. Indeed, it was found that mental imagery and working memory have shared representations in early visual cortex and therefore it is thought that presenting irrelevant visual information leads to a reduction in performance, since perceiving and remembering visual information occupy the same neural areas. This results in a competition of neural resources for remembering and precision of the representations. Furthermore, results of Pearson & Keogh (2019) confirmed that visual imagery was less precise when participants had to imagine more images simultaneously, and imagery was stronger when individuals imagined more similar arrays, suggesting that imagery is likely to be a dynamic resource.

The question why one chooses a strategy over another is something which needs further investigation. It can probably depend on the neurological makeup of one's brain. It is shown that individuals use different neural areas while performing a VWM task and differences can arise because some individuals have more efficient neural machinery (Pearson & Keogh, 2019). Variance in performance could also be explained by the current state an individual is in, for instance motivation. Moreover, the specific task and corresponding measurements have an impact on the different performances that occur since the used method and interpretation of result can vary drastically between studies and researchers. Another influencing factor could be previous experience, participants might use the strategy that has served them well earlier. Nevertheless, the assumption that humans process visual information in the same way has possibly led to disagreement and inconsistency in forming theories. Pearson & Keogh (2019) suggest a strategy-driven framework in describing VWM capacity which incorporates a variable for the cognitive strategy that is used when doing a VWM task. In this way, the mental processes are taken into account. Furthermore, Lockhart et al. (2020) propose a continuous allocation of resources that can flexibly be allocated with attentional priority and they suggest controlling attention is an individual strategy that subjects use when performing a VWM task. Notably, they state that any model of VWM capacity should take into consideration the individual differences in performance. Another study that emphasises the role of individual differences, although measured with short-term retention of verbal items, showed that individuals show markedly different patterns of self-reported strategy use for seven tasks from WM literature (Morrison et al., 2016). The findings support substantial variation across individuals for a given WM task, and within the same individual across tasks. This result should be taken into account carefully when interpreting findings from WM paradigms and consequently, these findings have as well significant implications for visual working memory. Overall, the three precedent studies highlight a shift in the debate that places greater emphasis on individual differences in VWM capacity, that can occur due to variation in strategy use.

4. Conclusion

The role of individual differences in visual working memory capacity is widely spread in existing research. However, within the models that try to describe VWM capacity, the strategies which are for a great deal responsible for the differences in performance, are not incorporated. Although object-fits-slot theories are suitable for full object representations in memory and an upper limit in item storage is found, the discrete models have no explanation for complex stimuli. Chunking as a strategy makes it hard to define which features are grouped together and how they could fit into slots. The CDA amplitude seems to be a predictor for the number of active representations in memory for high- and low-capacity individuals. However, the continuous models are more suitable to explain variability in performance across individuals. Flexible allocation could account for individual differences and in addition, when set size increases, studies did not find a guessing strategy, which reflects a dynamic resource. Eventually, the discrete models might seem too 'simple' to explain VWM capacity which has such a complex structure. However, it is important to stress the fact that both models are not yet able to offer a full understanding of how the strategies are possibly incorporated in their description of VWM capacity.

Ultimately, if the debate is to be moved forward, a better understanding of the different storage strategies for VWM capacity needs to be developed. There are still many related questions that remain unanswered. Further research should be carried out to establish different aspects of VWM capacity in order to make the discussion stronger founded. First, a recommendation for future work is: evaluating the format of (complex) stimuli. Previous studies investigating the structure of representations observed somewhat inconsistent results on whether subjects encode single features like colour and shape or integrated objects. Further work should discover the structure and format of representations in to fully understand the architecture of memory. Without knowing the specific make-up of items, it becomes problematic to ask other questions like whether there exists an item limit and to what extent is a possible resource spreaded? Secondly, another direction would be to focus on strategies to approach a VWM task. It is noteworthy that the purpose of this paper is not to provide an exhaustive list of strategies and it is certainly possible that there are additional visual memory strategies to investigate. Besides, chunking and visual imagery have both emerged relatively recently in literature and therefore need further investigation. For instance, chunking is well defined for numbers or letters, but not yet for feature encoding. To gain insight in cognitive approaches, more possible strategies should be evaluated. Besides, why humans use one strategy over another and how consciously this process is, should be considered.

This review demonstrates the need for better incorporating the role of encoding strategies, which requires a new reflection of the existing models. The underexposed strategy aspect of the debate should be examined with the aim to focus on the different cognitive processes of an individual. Here, it is important to keep in mind that besides the two main classes, variations of models are possible and should be considered in future work.

A last issue to address is that VWM capacity studies predominantly make use of the same working memory paradigm which should partially ensure consistency among results. However, the main issue lies with interpreting the findings. Different kind of errors are found and variation in quality of performance is often shown. These occur since subjects use different strategies, and when continuing the research in the same way, the results will only lead to more inconsistent outcomes. As long as the individual differences cannot be better explicated, there will be no additional clarity in the debate.

In conclusion, the results of the current study provide support for taking into account the encoding strategies of individuals when constructing VWM capacity models, with the consequence of moving the debate towards a more complete understanding of visual working memory capacity. Comprehension of human visual information processing has implications for cognitive psychology. Justified theories can be formulated to gain insight into overall cognitive ability. With the aid of those theories, algorithms can be designed for implementing cognition in AI-systems with the result that AI reaches its goal to create human-like behaviour.

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