How Episodic and Working Memory Affect Rule- and Memory-Based Judgments

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Abstract

Making accurate judgments is an essential skill in everyday life. However, little is known about the basic cognitive skills required for accurate judgments. Research on judgment and categorization processes suggests that people rely on various strategies when making judgments. These strategies differ in the cognitive abilities they require. Specifically high working memory capacity may benefit rule-based judgments, whereas good long-term memory may be crucial for memory-based judgments. We investigated this hypothesis following an individual differences approach. 177 participants performed two judgment tasks that were either best solved by a rule-based or a memory-based strategy. Additionally, we measured working memory capacity and episodic memory with three tests. Consistent with our hypothesis structural equation modeling showed that working memory capacity predicted judgment accuracy in the rule-based task whereas episodic memory predicted judgment accuracy in the memory-based task. Apparently, different memory abilities are essential for successfully adopting different judgment strategies.

Keywords: Judgment and decision making; working memory; episodic memory

Long-term memory and working memory are to a varying degree engaged in many daily activities. On a shopping trip, for example, people need episodic long-term memory to remember items on the shopping list. Trying to quickly sum up the prices of a shopping basket, however, draws upon working memory. Similarly, everyday judgments, such as judging the skills of a job candidate or the suitability of an apartment, may require both working memory and episodic memory. In this paper, we investigate how memory skills relate to people's success in solving judgment tasks.

Multiple Cue Judgments

In multiple-cue judgment tasks, people are asked to repeatedly estimate a continuous criterion such as the price of a shopping basket based on a number of cues, for instance the products in the shopping basket. To make such judgments, recent research suggests that people rely on two kinds of judgment strategies: rule-based and memory-based strategies (Juslin, Karlsson, & Olsson, 2008; von Helversen & Rieskamp, 2008).

Rule-based strategies assume that people try to explicitly abstract the relationship between the cues and the criterion and integrate this information in a linear additive way. To estimate the price of a shopping basket, for instance, the shopper may try to estimate the price of each product and add up all prices. Mathematically, this integration process can be described with a linear additive model. The criterion estimate $\hat{c}_p$ of an object p is the weighted sum of the cue values x_{pi}:

$$\hat{c}_p = k + \sum_{i=1}^{I} w_i \cdot x_{pi} \tag{1}$$

where w_i are the cue weights for each cue i and k is a constant intercept.

In contrast, memory-based strategies assume that people judge a new object (the probe) by retrieving previously encountered objects (exemplars) from memory. For example, when estimating the price of a shopping basket people may recall how much they spent the last time they went shopping. The more similar a retrieved exemplar (previous shopping baskets) is to the probe (current shopping basket), the more this exemplar influences the probe's criterion estimate. If a shopper bought the same items last time, for instance, he may just recall this price from memory to estimate the new prize.

This judgment strategy is mathematically described with an exemplar model (Juslin, Olsson, & Olsson, 2003). To determine the similarity, first the distance d_{pj} between the probe p and exemplar j is calculated. This distance is the summed absolute difference of their cue values x_{pi} and x_{ji} on each cue i, weighted by a sensitivity parameter h.

$$d_{pj} = h\left(\sum_{i=1}^{I} \left| x_{pi} - x_{ji} \right| \right) \tag{2}$$

These distances are then transformed into similarities $S(p,j)$ with an exponential decay function (Nosofsky & Zaki, 1998):

$$S(p,j) = e^{-d_{pj}} \tag{3}$$

To estimate the criterion value $\hat{c}_p$, the similarities are weighted with their corresponding criterion values c_j and averaged (Juslin et al., 2003).

$$\hat{c}_p = \sum_{j=1}^{J} S(p,j) \cdot c_j \Bigg/ \sum_{j=1}^{J} S(p,j) \tag{4}$$

Past research suggests that people shift between rule-based and memory-based judgment strategies depending on task structure (Juslin et al., 2008; von Helversen & Rieskamp, 2008). In linear additive judgment tasks, that is in tasks where the criterion can be approximated by a linear additive function of the cues, people generally rely on rule-based strategies. In contrast, in multiplicative judgment tasks, where the criterion can be approximated by a multiplicative function of the cues, memory-based strategies are more frequently used (Hoffmann, von Helversen, & Rieskamp, 2013; Juslin et al., 2008). However, little attention has been paid to the cognitive abilities these strategies draw upon and how individual differences in cognitive abilities influence strategy selection and performance.

Memory Processes in Multiple-Cue Judgments

Theories in judgment and categorization propose that rule-based and memory-based judgment strategies build on different memory abilities. For instance, Ashby and O'Brien (2005) suggested that executing simple rule-based categorization strategies requires working memory capacity, whereas exemplar retrieval involves episodic memory. In a similar vein, Juslin et al. (2008) argued that cue abstraction could be conceived as a capacity-constrained sequential process, whereas memory-based judgment strategies rely on a controlled retrieval process.

Previous research has often studied how working memory influences judgment and categorization performance. In line with a capacity-constrained abstraction process, cognitive load impairs performance in rule-based categorization tasks more than performance in implicit information-integration tasks (Zeithamova & Maddox, 2006). Indeed, cognitive load may even induce people to shift from a rule-based to a memory-based strategy suggesting that memory-based strategies require less cognitive control (Hoffmann et al., 2013). Yet, some research also suggests that working memory may play a crucial role in learning in all judgment tasks. Indeed, performance in a range of judgment tasks can be predicted by measures of working memory and intelligence (Weaver & Stewart, 2012). Similarly, Lewandowsky (2011) found that high working memory capacity benefitted learning in rule-based as well as memory-based categorization tasks. Thus, it is unclear whether high working memory capacity only benefits rule abstraction processes or whether it benefits performance in all kinds of judgment tasks.

Research relating episodic memory to judgment performance is scarce. Exemplar models predict a relationship between recognition and categorization and, indeed, have successfully modeled both recognition and categorization performance (Nosofsky, 1988). Consistent with a controlled retrieval process, the instruction to learn all exemplars by heart improves performance in a difficult memory-based judgment task (Olsson, Enkvist, & Juslin, 2006). Also, memorization of single exemplars enhances recognition of these exemplars in a later recognition test (Palmeri & Nosofsky, 1995). The importance of episodic memory for category learning, however, has been severely disputed (Knowlton, 1999), leading to a call for more experimental studies (Ashby & O'Brien, 2005). Taken together, although some evidence suggests that people engage in a controlled retrieval process when solving memory-based judgment tasks, the role of episodic memory in categorization and even more for judgments is still unclear.

The Present Study

Our study investigates how episodic and working memory skills affect judgment performance in rule-based and memory-based judgments. We test the hypothesis that judgment accuracy is related to working memory capacity when people rely on a rule-based judgment strategy. Likewise judgment accuracy should be related to episodic memory when people adopt a memory-based judgment strategy. To test these hypotheses, the participants solved a linear as well as a multiplicative judgment task. In addition, we measured participants' working memory and episodic memory skills using three different tests.

Participants

177 participants (113 female, M_{Age} = 24.1, SD_{Age} = 6.2) were recruited at the University of Basel. Participants received a participation fee of 20 CHF per hour (approx. 22 US-$) and an additional bonus in the judgment tasks (M = 10.3, SD = 2.4). One subject was excluded from the analysis because he guessed in the judgment tasks.

Automated Working Memory Span Tasks

Working memory span tasks were designed to measure both storage and processing of information in working memory (Redick et al., 2012). In working memory span tasks, participants process one set of stimuli while remembering another set of stimuli. For instance, in each trial of the operation span task, participants first see a simple equation. After they have solved the equation and given the answer, they see the first letter that has to be remembered. Subsequently, another equation is presented and another letter has to be remembered, until the set size (the number of presented letters) is reached. Finally, participants are asked to recall the letters in the order of their appearance. Trials with different set sizes are randomly interspersed, with each set size repeated three times. All span tasks were taken from Unsworth et al. (2009) and translated to German.

Reading Span In the reading span participants judged the plausibility of a sentence while remembering letters. Set size varied from 3 to 7.

Operation Span Participants were asked to solve mathematical equations while remembering letters. Set size varied from 3 to 7.

Symmetry Span Participants judged the symmetry of a chessboard picture while remembering the position of squares in 4 x 4 matrix. Set size varied from 2 to 5.

Episodic Memory Tasks

We measured episodic memory with three different tasks: a free recall task with pictures, a cued recall task with numbers, and a recognition test of verbs.

Picture Free Recall We selected 20 pictures from a picture database (Rossion & Pourtois, 2004) that had high ratings on imagery and concreteness. Each picture was presented for 3 s on the screen and participants were asked to remember them. After a retention interval of 2 minutes participants recalled the pictures.

Cued Number Recall We assessed cued number recall with a computerized version of the Cued Number Recall task from the BIS 4 (Jäger, Süß, & Beauducel, 1997). 15 pairs of a two- and a three-digit number were presented for 10 s each on the screen. After a retention interval of 2 minutes participants saw the cued number pair as well as four three-digit distractors and had to indicate which three-digit number was initially presented together with the two-digit number.

Verb Recognition We selected 40 verbs with 5 to 7 letters from the Hager and Hasselhorn database (1994) rated high on imagery and concreteness. Participants learned half of the verbs for 3 s each. After a retention interval of 2 minutes participants indicated whether they recognized the 40 verbs from the learning phase by classifying them as *old* or *new*.

Judgment Tasks

Participants solved both a linear and a multiplicative judgment task. In the linear judgment task, we expected participants to use a rule-based strategy; that is, their judgments should be well described by a linear regression model. In contrast, in the multiplicative judgment task, participants should rely on a memory-based strategy (Juslin et al., 2008).

In the linear judgment task, the criterion y was a linear, additive function of the cues and could thus be perfectly predicted by a rule-based strategy:

$$y = 4\, c_1 + 3\, c_2 + 2\, c_3 + c_4 \quad (5)$$

where c_1 reflects the most important cue according to its cue weight. Each cue value varied between 0 and 5.

In the multiplicative judgment task the function generating the criterion y included a multiplicative combination of the cues:

$$y = \left(4c_1 + 3c_2 + 2c_3 + c_4 + 2c_1c_2c_3 + c_2c_3c_4\right)/8.5 \quad (6)$$

Because of the interacting cues, abstracting linear additive rules does not help solve the task. Therefore, people should switch to exemplar-based strategies and store the objects and the associated criterion values in exemplar memory (Juslin et al., 2008).

We used two different cover stories for the linear and the multiplicative multiple-cue judgment task. In the linear judgment task, participants judged how well a comic figure performed in a game on a scale from 0 to 50. In the multiplicative judgment task, participants estimated how toxic a bug was on a scale from 0 to 50. The stimuli for the two cover stories consisted of pictures of either bugs or comic figures. These bugs and comic figures varied on four different continuous cues. The bugs varied on the length of their legs, their antennae, and their wings and the number of points on their back. The comic figures had different sizes of their ears and their nose, a different number of hairs and stripes on their shirt. These visual features were randomly assigned to the cues.

Both tasks consisted of a training phase and a test phase. During the training phase, participants learned to estimate the criterion values for 25 exemplars. In each trial, participants first saw a picture of a bug or a comic figure and were asked to estimate its criterion value. Afterwards they received feedback about the correct value, their own estimate and the points they earned. The training phase ended after 10 blocks. In the subsequent test phase, participants judged 15 new probes four times, but did not receive any performance feedback.

To motivate participants to reach a high performance, participants could earn points in every trial. The number of points they earned was a truncated quadratic function of the deviation of their judgment j from the criterion y:

$$\text{Points} = 20 - (j - y)^2/7.625 \quad (7)$$

At the end of the judgment tasks, the points earned were converted to a monetary bonus (1500 points = 1 CHF). In addition, participants earned a bonus of 3 CHF if they reached 80% of the points in the last training block.

Procedure

Participants solved all tasks on one day with half an hour break between the two sessions. The tasks were presented in the same order to each participant. In the first session, participants began with the linear judgment task, moved on to the operation span, solved the verb recognition and the picture free recall task, and finally completed the symmetry span. The second session started with the multiplicative judgment task. Afterwards, participants completed the reading span and finally the cued number recall task.

Results

Task Performance

We first analyzed participants' average performance in the memory and the judgment tasks (see Table 1 for descriptive statistics). In the working memory tasks, we used the partial credit score, the sum of items recalled in the correct position, as the dependent variable (Conway et al., 2005). If a participant recalled all items correctly, he achieved a score of 75 in the operation span and the reading span and a score of 42 in the symmetry span. Overall, participants recalled more items in the operation and the reading span than in the symmetry span, replicating normative data (Redick et al., 2012). In the episodic memory tasks, we used the percentage of correctly recalled items as the dependent variable. On average, participants remembered a higher

Table 1: Descriptive statistics for the memory and the judgment tasks.

Task	*M*	*SD*	Skew	Kurt
Operation Span	57.7	12.3	-1.2	1.7
Reading Span	57.1	12.2	-1.8	2.3
Symmetry Span	29.6	7.4	-0.6	0.1
Recognition (% recalled)	.87	.09	-0.7	0.5
Cued Recall (% recalled)	.42	.19	0.2	-0.2
Free Recall (% recalled)	.46	.17	0.1	-.01
Linear Judgment				
Last training block	6.0	2.2	0.9	1.9
Test (Mean)	5.4	1.8	0.7	0.8
Multiplicative Judgment				
Last training block	5.2	1.8	0.7	0.6
Test (Mean)	5.0	1.8	1.0	0.8

Note: Skew = Skewness; Kurt = Kurtosis

percentage of items correctly in the recognition task than in the cued recall or the free recall task.

Learning performance in the judgment tasks was measured with the root mean squared deviation (RMSD) between participants' judgments and the correct criterion in the last training block. The learning performance showed that on average participants learned the judgment tasks quite well. However, the multiplicative judgment task was learned more easily than the linear judgment task. Could participants generalize this good performance to judgments for new items in the test phase? We measured judgment performance in the test phase as the RMSD between the correct criterion and participants' mean judgments; that is, the judgment for each probe averaged over the four presentations in the test phase. Performance for new items in the test phase was comparable to performance in the training phase indicating that participants successfully generalized their performance to new items.

To determine which judgment strategy described participants' judgments best, we fitted a linear regression model (see equation 1) and an exemplar model (see equations 2-4) to participants' judgments in the last three training blocks and predicted participants' mean judgments in the test phase (von Helversen & Rieskamp, 2008). We compared those models to a baseline model that simply estimated participants' mean judgment. Participants were classified as following the strategy that led to the smallest RMSD between model predictions and participants' mean judgments in the test phase. As shown in Figure 1 the judgment process of the participants was highly task sensitive: In the linear judgment task most participants were best described by a linear model, whereas in the multiplicative judgment task, most participants were best described by an exemplar model, $\chi^2(2) = 95.3$, $p < .001$.

Measurement Models

To understand which memory abilities underlie human judgment processes we followed a structural equation

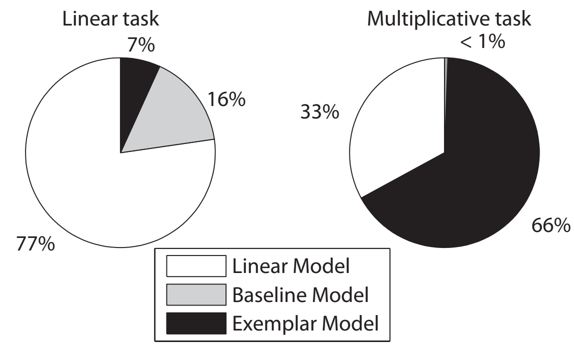

Figure 1. Strategy classification of participants in the linear and the multiplicative judgment task.

modeling approach. Structural equation modeling allows detecting relationships between latent constructs while correcting for the distinct variance of the measures (for a review see Tomarken & Waller, 2005).

We first estimated two separate measurement models for memory and judgment abilities. These models were later combined into one structural model. All models were estimated using a maximum likelihood estimator with robust standard errors (MLR) because descriptive data indicated some deviations from multivariate normality. The reported χ^2 difference tests were performed using the Satorra-Bentler scaled χ^2 values (Satorra & Bentler, 2001).

Measurement Models for Memory Abilities To measure memory abilities, we hypothesized that episodic memory and working memory capacity can be conceived of as two separate latent constructs that may be correlated (Brewer & Unsworth, 2012). We first fitted a two-factor latent variable model to the memory data assuming no correlation between working memory and episodic memory. All working memory span tasks loaded on one latent factor, while all episodic memory tasks loaded on a second latent factor. Because the residual variance of the manifest variable recognition was estimated to be negative, we fixed it to 0. This model fitted reasonably well, $\chi^2(10) = 16.11$, $p = .10$, CFI = .95, RMSEA = .06, SRMR = .08. Allowing working memory capacity and episodic memory to correlate did not significantly improve model fit, $\chi^2(9) = 14.85$, $p = .10$, CFI = .95, RMSEA = .06, SRMR = .06. Finally, a one-factor model assuming a correlation of 1 between episodic memory and working memory capacity fitted worse than the two-factor model, $\chi^2(10) = 128.2$, $p < .001$, CFI = .01, RMSEA = .26, SRMR = .16. In sum, memory abilities in our study were best described by assuming two separate, uncorrelated latent constructs for working memory and episodic memory.

Measurement Models for Judgment Abilities To find out whether performance depends on the judgment task, we fitted three different measurement models for judgment abilities to judgment performance in the four test blocks of the linear and the multiplicative judgment task. We first estimated a two-factor latent variable model assuming no

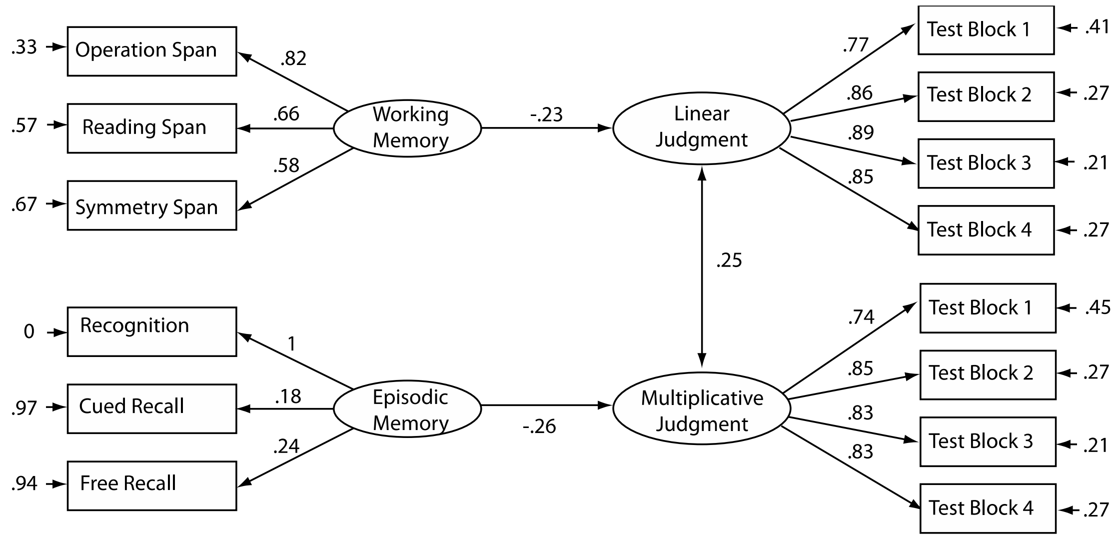

Figure 2: Structural equation model relating working memory capacity and episodic memory to judgment performance in the test phase. All loadings and correlations are standardized.

correlation between the factors. One factor predicted judgment performance in the linear judgment task, the second factor predicted judgment performance in the multiplicative judgment task. This model did not describe the judgment data well, $\chi^2(20) = 38.54$, $p < .01$, CFI = .975, RMSEA = .07, SRMR = .11. Allowing a correlation between the judgment factors improved model fit, $\chi^2(19) = 28.24$, $p = .08$, CFI = .99, RMSEA = .05, SRMR = .03. Finally, we estimated a one-factor model assuming a correlation of 1 between judgment performance in the linear and the multiplicative task. This one-factor model could not account for the judgment data, $\chi^2(20) = 362.14$, $p < .001$, CFI = .54, RMSEA = .31, SRMR = .22. In sum, a two-factor model with correlated factors captured performance variations within the judgment tasks best. This suggests that although performance in rule-based and memory-based judgment tasks is correlated, distinct processes may account for performance differences between the tasks.

Linking Memory Skills to Judgment Performance

Next, we investigated the link between memory abilities and judgment performance. Based on our prediction, we estimated a structural model (depicted in Figure 2) relating working memory capacity to judgment performance in the linear task and episodic memory to judgment performance in the multiplicative task. This model provided a good fit to the data, $\chi^2(75) = 89.93$, $p = .12$, CFI = .98, RMSEA = .03, SRMR = .08. Allowing a correlation between working memory capacity and judgment performance in multiplicative tasks and a correlation between episodic memory and judgment performance in linear tasks did not significantly improve the fit of the structural model, $\chi^2(73) = 85.27$, $p = .15$, CFI = .99, RMSEA = .03, SRMR = .06. Also, a structural model assuming that memory abilities do not predict judgment abilities could not account for the data, $\chi^2(77) = 107.48$, $p = .01$, CFI = .97, RMSEA = .05, SRMR = .10. Indeed, setting the weight from working memory to linear task performance to 0 decreased model fit, $\Delta\chi^2(1) = 4.10$, $p = .04$. Likewise, setting the weight from episodic memory to multiplicative task performance to 0 decreased model fit, $\Delta\chi^2(1) = 12.67$, $p < .001$. Thus, while judgment accuracy in rule-based tasks was predicted by working memory capacity, judgment accuracy in memory-based tasks was predicted by episodic memory.

Discussion

Our study sheds light on which memory abilities people rely when making judgments, a topic that has received little attention in the literature. As the first study linking memory abilities to performance in judgment tasks, we found that working memory capacity predicted judgment accuracy in a linear task, whereas episodic memory predicted judgment accuracy in a multiplicative task. Furthermore, participants relied on a rule-based strategy in the linear task and a memory-based strategy in the multiplicative task. In line with theories of judgment and categorization (Ashby & O'Brien, 2005; Juslin et al., 2008) this suggests that the two strategies draw upon different memory abilities.

Our results suggest that working memory capacity only predicted judgment performance in rule-based judgment tasks. This result seems to contradict research linking working memory capacity to performance in rule-based and memory-based categorization tasks (Lewandowsky, 2011). One reason for these diverging results may be that our study focused on the differences between judgment tasks, namely the covariance that was not explained by a common judgment factor. Yet, Lewandowsky concentrated on the similarities among categorization tasks. Another reason for these diverging results may be that our study focused on the generalization to new items instead of the learning process. Indeed, in Lewandowsky's study a learning parameter was strongly related to working memory capacity. Thus, while learning to apply a rule-based or a memory-based judgment strategy may require working memory capacity, only the correct execution of a rule-based judgment strategy may draw upon working memory capacity. Executing a memory-based judgment strategy may instead involve episodic memory skills.

Few studies have examined the link between episodic memory and judgment abilities. Our study clearly shows that episodic memory is related to performance in memory-based judgments. This result highlights the importance of episodic memory for judgments and resonates well with theories suggesting that exemplars are stored and deliberatively retrieved from long-term memory (Juslin et al., 2008). It is also in line with research arguing for exemplar processes in categorization (Nosofsky & Zaki, 1998). Beyond that, our results highlight that a multitude of cognitive skills, not only working memory, is involved when people make judgments. Shifting the focus to long-term memory may open up new research questions and applications. For instance, memory-based judgment strategies may be more vulnerable to forgetting and interference. Knowledge about storage and retrieval processes in judgment may thus help improving judgments ranging from simple daily judgments such as estimating the price of a shopping basket to professional judgments such as judging the quality of a job candidate.

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