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How to investigate insight: A proposal

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Abstract

One of the most challenging issues in the field of creativity is finding an approach conducent to understanding the cognitive and neural mechanisms underlying insight. We propose investigating the process of insight within the context of implicit learning paradigms. The training tasks in implicit learning paradigms are regularly constructed and, although participants are not informed about the existence of such a regularity, some of them gain insight into this regular pattern during training. This process of spontaneously arising explicit knowledge during an incidental learning situation strongly resembles the process of finding the solution for an insight problem. The main advantage of these incidental learning situations is the opportunity to investigate the process of insight on a trial-by-trial basis. This would be of particularly interest to researchers who want to relate the process of insight to neural activity. We begin with a description of our main findings concerning the emergence of explicit knowledge in implicit learning and continue with detailed descriptions of our implicit learning paradigm and data-analytic strategies.

Keywords: Creativity; Insight; Implicit learning; Insight problem-solving

1. Introduction

Almost everyone would agree that creativity refers to producing something that is new, original and worthwhile, like important scientific discoveries or famous artistic works. Accordingly, most researchers assume that creative solutions can be characterized by two important features: novelty and appropriateness of a solution for a problem [e.g., 1–3]. Furthermore, novelty is generally assumed to result from a novel combination of information that abruptly comes into mind as an insight and that requires verification of its appropriateness [e.g., 1]. However, it is not known yet, how cognitive processes might produce such an abruptly occurring insight. Understanding the processes underlying the development of insight therefore is one of the most challenging issues in the field of creativity. Thus, an important question is how to best investigate the process of insight.

In cognitive psychology, many researchers focus on this process of insight by studying insightful problem-solving [e.g., 4–6]. The important advantage of studying insight problem-solving rather than creativity itself is that it enables researchers to experimentally examine the process of insight within a relatively short time period.

The purpose of the following article is to propose a new way of investigating the process of insight within a short time period, namely, to examine the process of insight using implicit learning tasks, such as the serial reaction time task (SRTT, [7]) or the number reduction task (NRT, [8]). At first glance, this may seem strange—particularly for researchers familiar with implicit learning—as implicit learning tasks are normally used in order to investigate the characteristics of implicit learning. However, on closer inspection of results from implicit learning experiments, between 10% and 70% of all participants—with the exact percentage varying with experimental condition—are able to verbally describe the deterministic regularity built into

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the task when asked to do so in a post-experimental interview. Usually, researchers in the field of implicit learning are not interested in these participants. Rather, they exclude them from further data-analyses because these participants possess explicit knowledge about the underlying regularity and thus might contaminate the investigation of implicit learning.

As we will argue, participants developing explicit knowledge within an incidental learning situation are particularly interesting as during training they develop an abruptly occurring insight into the underlying regularity. Thus, like in insight problem-solving, participants exhibit an insight during the experiment. However, one of the main and most important advantages in using an implicit learning paradigm instead of insightful problem-solving is that it will enable researchers to pursue the development of an insight on a trial-by-trial basis. This would provide researchers with an opportunity to relate the dynamic development of insight to neural activity.

In the following article, we first describe the rationale underlying our research. To do so, we briefly summarize our experimental results and discuss differences and commonalities between our experimental paradigm and insightful problem-solving. We then describe in further detail the number reduction task, which is an implicit learning task we have been using in our experiments. Furthermore, we show how this experimental task can be used to investigate the process of insight on a trial-by-trial basis. We end with a brief discussion of the advantages and disadvantages of the NRT as compared to other implicit learning paradigms such as the well established serial reaction time task.

2. Survey of our research on insight within implicit learning situations

The main goal of our research is to describe some of the mechanisms that link the experience of an environmental regularity to the ability to verbally report the regularity [8–11]. More specifically, we focus on mechanisms that lead to verbally expressible knowledge about a regularity within an incidental learning situation. It is important to note that the term “verbally expressible knowledge” refers only to participants’ ability to *deliberately* describe the underlying regularity in a post-experimental interview. In this interview, participants are only asked whether they noticed anything during the experiment. They are not explicitly instructed to describe the underlying regularity because we assume that any question about the regularity might cause participants to start thinking about the existence of such a regularity [12]. By contrast, participants who are able to deliberately describe the underlying regularity in this post-experimental interview are those who already have developed explicit knowledge during the incidental learning situation. As we will show below, the development of explicit knowledge arises abruptly and resembles the process of finding the solution for an insight problem.

The starting point of this research were results from experiments in cognitive skill acquisition. The specific feature of the tasks presented in these experiments was that they always followed a regular abstract pattern. If a participant detects this abstract pattern, it can be used to establish a much easier strategy to process the tasks. For example, the alphabetic verification task [10,13] contains task-relevant and task-irrelevant information. Specifically, the items (letter strings such as e.g., “C D E F G [4] L”) to be evaluated in the alphabetic verification task consist of a relevant letter-digit-letter triplet (e.g., “G [4] L”) and a varying number (0, 1, 2, 3, or 4 letters) of additional letters (e.g., “C D E F”). The additional letters are, due to the fact that errors never occur in these letters, irrelevant with respect to the evaluation of the strings. Thus, a participant who discovers this regularity can evaluate the alphabetic verification task by only verifying the letter-digit-letter triplet while ignoring the additional letters. Importantly, participants are typically not informed that the additional letters are irrelevant to the verification task. Rather, they are only told how to verify the target letter strings; that is, to count through the alphabet and to interpret the digit in the letter-digit-letter triplet as the number of letters that need to be skipped before continuing on with the alphabet.

The results of these first experiments revealed that the learning functions of some participants clearly violated the power law of practice typically found in experiments in cognitive skill acquisition [14]. While the power law of practice assumes that participants’ response times follow a continuous, negatively accelerated learning function, the response times of these participants decreased slightly at the beginning of training and then showed an abrupt steep drop (hereafter RT-drop). Furthermore, in a post-experimental interview, exactly these particular participants were able to deliberately name the regularity that guided the construction of our tasks. By contrast, participants who did not produce such an RT-drop during training were not able to verbally describe the underlying regularity [13].

In further experiments we focused on the meaning of these RT-drops. Our hypothesis was that they might reflect a qualitative change in strategy use which is due to a more or less abruptly occurring insight into the regularity of how the tasks are constructed. This hypothesis gained some support from observations that participants sometimes reported an “Aha!” effect, which is characteristic for many types of cognitive processes in various forms of creativity and insightful problem-solving [15].

In a first series of experiments, we investigated whether the RT-drops are correlated with qualitative changes in performance. To this end, we trained participants with the number reduction task (NRT). In the NRT (further explained below), participants are instructed to generate several responses in order to compute the final response for the given task. As in the alphabetic verification task, the tasks follow a regularity: The responses produced for a given task always follow the same abstract pattern (e.g., the second respond is always identical to the final response, such that participants can stop after having computed the second response). Again, participants are not informed about this regularity. However, a participant who discovers the regularity can use a much easier strategy in order to compute the final response. As in the alphabetic verification task, we expected participants who discover this regularity to exhibit an RT-drop during training. Therefore, participants were trained until they produced such an RT-drop or until their training duration exceeded a fixed number of practice blocks (5 practice blocks in this experiment) [13]. If a participant exhibited an RT-drop before reaching the fifth training block, he or she received one more practice block and then was given two transfer blocks containing new tasks. If not, he or she received the two transfer blocks after finishing the fifth training block. The tasks in these transfer blocks either followed the construction principle of the tasks in the training blocks or were randomly constructed (between participants). Results confirmed that participants with an RT-drop (35% of the participants) during training were much faster in responding to the new structure-equivalent tasks than participants without such an RT-drop during training (65% of the participants). By contrast, if participants with an RT-drop received randomly constructed tasks in the transfer blocks their response times dramatically increased and did not differ from those of participants without an RT-drop.

A second study in which we also interrupted participants' training immediately after they had exhibited an RT-drop showed that these participants were able to deliberately describe the regularity in a post-experimental interview. By contrast, participants without an RT-drop were not able to do so, even though their training duration was much longer [10]. Thus, the RT-drop signals a qualitative change in task performance which appears to be caused by an insight into the underlying regularity.

We then focused on the mechanisms underlying the RT-drop. One might assume that the RT-drops simply result from the strengthening of the implicitly acquired representation of the regularity which, if strong enough, pops into consciousness [16,17]. In this case, the abrupt RT-drop and the insight into the underlying regularity are an obligatory consequence of task practice. However, it is also conceivable that strengthening of memory representations alone is not sufficient for the insight to occur. For example, insight in insightful problem-solving is assumed to be based on restructuring of task representation, rather than on strengthening of memory representations [4,5,18]. Therefore, we examined whether strengthening of memory representation is sufficient in order to explain the appearance of an insight within the NRT.

At least descriptively, two of our findings argue against strengthening as the sole mechanism underlying the occurrence of RT-drops. First, even when we tripled training duration, the number of participants who exhibited an RT-drop during training only increased by 10% (with an identical training procedure, the number of participants with an RT-drop increased from around 60% with 9 training blocks to around 70% with 27 practice blocks). According to the strengthening assumption, one should expect to find a higher increase in the rate of participants with an RT-drop. Second, in a recently conducted experiment [11], we manipulated the interval between a participant's response and the occurrence of the next stimulus (response stimulus interval, RSI). Basically, it is assumed that prolonging the RSI should reduce strengthening due to increased memory decay, ultimately resulting in a reduction in the number of participants with an RT-drop [19]. However, results of our RSI-experiment showed that—contrary to the strengthening assumption—significantly more participants in the long RSI condition exhibited an RT-drop and were able to verbally describe the underlying regularity. On the basis of this finding, we suspect that implicit learning processes lead to advanced response preparation; that is, the last response already triggers the next response even before the next stimulus appears on the screen. The longer the RSIs, the further this response preparation has progressed. Consequently, in the long RSI condition, this response preparation might increase the probability of premature responses (i.e., responses that occur in advance to or shortly after the appearance of the imperative stimulus). However, as the learning is implicit, participants should not be aware of this ongoing implicit learning process and thus should be surprised about such unexpectedly fast and correct responses. We further assumed that exactly this surprise about such fast and correct responses triggers a search process for possible causes. This search, or attribution process, leads in turn to the insight into the underlying regularity [8].

In order to test this assumption, we replicated the RSI-experiment with one modification: Whereas participants in the former experiment were allowed to respond within the RSI, we now hindered participants from responding prematurely. That is, participants could respond only after appearance of the imperative stimulus. If our suggestions above are correct and the increased number of participants with an RT-drop in the long RSI condition was due to the increased opportunity for premature responses, then we should find now no difference between the long and the short RSI conditions. The results of this replication exactly confirmed our expectation: the short and long RSI-conditions did not differ; that is, in the replication, the long RSI did not increase the probability of an RT-drop or of correctly naming the underlying regularity [11]. This finding is consistent with the assumption that unexpected fast responses might trigger a search process that then leads to the insight into the systematic construction of the tasks. However, it is inconsistent with the assumption that RT-drops result solely from the strengthening of memory representations.

To summarize, our experimental results suggest that participants who were trained with regularly constructed tasks often discover this regularity without being informed about its existence. This insight into the regularity goes along with an RT-drop, indicating an abrupt change to an easier strategy in order to conduct the tasks at hand. Furthermore, the results suggest that the insight is not due to strengthening of memory representation alone. Rather, it seems that it requires a switch from implicit learning to explicitly searching for the regularity built into the tasks; that is, we suspect that—like in insight problem-solving—the insight in our experiments also requires some kind of restructuring of task representation.

One important advantage of using an implicit learning paradigm, like the NRT, in order to investigate the process of insight is that, in comparison to insight problem-solving, participants repeatedly conduct tasks of the same type. This repeated presentation of tasks provides a method for studying the process of insight on a trial-by-trial basis. By contrast, typical insight problem-solving experiments confront participants with one single task [6,20] or several tasks of one type [5]. The only available performance measures in these experiments are solution times or the probability of solutions, which only proved weak information about the process of the insight [21]. Some authors therefore have started to use alternative methods, like think-aloud protocols [4,22,23] or, most recently, eye movement recordings [21]. Although these methods allow the observation of the process of insight in a temporally more fine-grained manner, it is not clear yet whether or not they might change the actual process of insight [21,24].

However, the advantage of trial-by-trial data gained from such implicit learning tasks also comes with one important disadvantage. In insight problem-solving experiments, participants often stop for a while to actively explore the problem space before they discover the solution. This impasse-insight sequence is seen as one important characteristic of insight problem-solving [21,25]. By contrast, participants in implicit learning tasks always have to react to the tasks at hand; that is, even if they are stuck in an impasse concerning the discovery of the underlying regularity, they have to continue to process the task at hand. This makes it either difficult or impossible to detect whether a participant experiences an impasse. Thus, implicit learning tasks, as used here, are suited to investigating the processes underlying the occurrence of an insight, but are less suited to investigating the impasse-insight sequence. In the next section, we describe the implicit learning paradigm used in our experiments.

3. The implicit learning paradigm

In most of the above experiments, we used the so-called number reduction task (NRT; [8,9,11]) or derivates of this task [26–29]. In the standard version of the NRT, participants receive a string of six digits on a computer screen (see Fig. 1). The string always consists of the same three digits, "1", "4", and "9" arranged in a different order for each trial (e.g., "9 9 9 1 4 1"). The participants' task is to compute the final response for the entire string. To do so they are instructed to process the digit string pair-wise from left to right by applying the matching one out of two rules. The first rule states that two identical digits in a pair yield the same digit (Same-rule). The second rule states that the result for two non-identical digits is the remaining third digit (Different-rule). Participants are explicitly told these two rules.

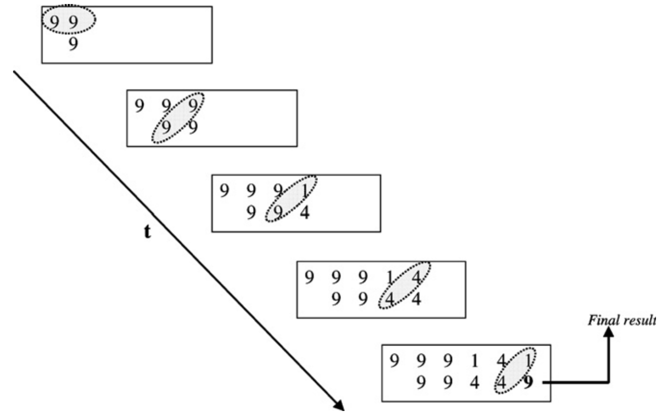

Fig. 1. The number reduction task (NRT).

In the example "9 9 9 1 4 1" depicted in Fig. 1, participants first receive the first two digits of the digit string. These two digits are identical, which complied with the Same-rule and leads to the result "9". After entering the response, the next digit of the digit string occurs on the screen. Participants now have to compare the result of the previous comparison (their previous response) with the new digit in the string. In the example "9 9 9 1 4 1", the outcome of the first comparison, the digit "9" is compared with the third digit in the string, also a "9". According to the Same-rule, this generates "9". The result of this comparison is again compared with the next digit in the string: "9" (previous result) and "1" (next digit in the string) yield "4" according to the Different-rule. When participants reach the last digit in the string, they produce their fifth and last response. Participants are instructed to confirm this last result as the final result of the entire string by pressing the "Enter"-key.

In the standard version of the NRT, while performing the tasks, participants incidentally experience the following regularity: On any given task, the fourth response is always identical to the third response, and the fifth response is identical to the second response. Put differently, participants' Responses 4 and 5 are a mirror image of Responses 2 and 3. Thus, across trials participants produce response patterns of the kind "9 9 4 4 9", "1 4 9 9 4", or "9 4 1 1 4".

In all of our experiments, this regularity within response strings is neither communicated to participants nor are they asked to search for any regularity that may be hidden in the task, making it an implicit learning task. Participants who discover the task regularity are able to speed up generation of the final response substantially. They can enter Responses 4 and 5 in very quick succession as these responses are determined by Responses 3 and 2, or they can skip Responses 3, 4, and 5 altogether as Responses 2 and 5 are identical (the latter is possible as participants are instructed to confirm the final result of the entire string with the enter-key, for clarification see below).

The experiments always start with a detailed explanation of how to compute the digit strings. Participants are told that their task is to compute the final result for a given string. To do so, they are given the two above described rules. They are instructed to confirm their last result with the enter-key signalling the computer program that this is the final result for the entire string. In addition, they are also told that they can press the enter-key whenever they believe that their last computed result is the final result.[1] They then receive ten randomly constructed practice trials in order to test whether or not they correctly understood the instructions. If a participant makes more than three errors, he or she is first asked whether he/she wants to repeat the instructions. Irrespective of the answer, the 10 practice trials are then repeated.

In most of our experiments participants then receive 7–9 practice blocks with 54 tasks each. Each task presentation starts with a number of dashes on the screen signalling the length of the digit string (i.e., 6 dashes in the case of six-digit strings). After a fixed interval of e.g., 500 ms, the first digit-pair appears on the screen and participants have to compute their first response. After a fixed interval (e.g., 500 ms), this response and the next digit of the digit string appear on the screen. Response and digit presentation continues until the participant presses the enter-key or until all digits of the digit string have been presented. Participants are allowed to enter more than 5 responses. Usually, number of responses is limited to 9 responses, and time to compute the final response is limited to 8 s. If a participant exceeds one of these limits, the digits disappear from the screen and an error-feedback appears on the screen. Then the next trial starts.

If a participant presses the enter-key in time, the digits on the screen remain for a further interval (e.g., 500 ms) and, if the final response—the response preceding the enter-key—is correct, the digit string and the response string turn blue. If the final response is incorrect, the color of the digit string and response string do not change. The digits on the screen then disappear and the next trial starts. Hence, if participants press the enter-key in time, they receive feedback about the correctness of their final response; all other errors within the response string are ignored.

Taken together, the NRT in its standard version is presented successively. That is, participants see a successively built-up string for the digit string and the response string. This successive presentation ensures that participants always have to compute all intermediate results as long as they do not know the underlying regularity. In addition, it allows the manipulation of the interval between a participant's response and the occurrence of the next stimulus-pair on the screen (see the above mentioned RSI-studies).

Moreover, this successive presentation of digit strings may be of particular interest if one wants to relate performance data to neural activity on a response by response basis. For example, in several fMRI studies, we compared the neural activity related to predictable versus unpredictable responses [26–28]. For this purpose, we used a constant interstimulus interval between consecutive stimulus pairs of 1.6 s; that is, the next stimulus pair (the response to the last stimulus pair and the next digit in the string) occurred after 1.6 s, irrespectively of whether or not a participant had entered a response within this interval. However, the task of the participants was to respond in advance of the presentation of the next stimulus-response pair.

The long and constant RSI was needed to avoid confounding effects of increasing stimulation speed on the fMRI signal [30]. However, in regard to insight, the results of these studies were somewhat disappointing as participants did not gain insight into the underlying regularity. We suspect that this might be due to the extreme noise of the scanner inherent in an fMRI experiment. In addition, it may be that the fixed interstimulus interval requires participants to wait for the next stimulus before they can compute their next response. The main difference between this version and the standard version of the NRT is that the latter allows participants to enter their responses to the predictable input positions in quick succession without waiting for the next stimulus. If a participant in the standard version of the NRT responds in advance to the imperative stimulus (the response digit and the next digit in the digit string) then these two digits always occur immediately after the response key was pressed. Hence, a participant can enter responses in very quick succession without waiting for another stimulus. In the fMRI-studies, this speed-up of interstimulus intervals interferes with the constraints for the analyses of the BOLD signal. This is a clear disadvantage of the NRT.

However, we recently found a solution for this problem by using a much easier version of the NRT [31]. In this study, we used a version of the NRT that only consists of five-item strings composed of squares in 3 different colors. That is, the digits 1, 4, and 9 of the standard NRT were replaced by blue, green, and red squares. The abstract regularity built into the response string was that the first response was always identical to the fourth (last) response. Discovering the underlying construction principle within this colored-squares NRT is much easier and refers only to the last input position. Consequently, even with an interstimulus interval of 3 s, participants developed an insight into the underlying regularity. This extremely long interstimulus interval of 3 s, however, allowed us to relate the performance data of each single response to neural activity and thus to analyze brain activity related to developing insight.

Overall, the superficial features of the NRT (e.g., numbers as stimuli) as well as the regularity built into the task

[1] One might suspect that this additional instruction might serve as a hint that a short-cut exists for computing the tasks. However, we interrupted several participants after they had read the instructions and asked them what they remembered about them. All these participants could explain the task and how to compute the final response. None of them reported that they suspected a short-cut for computing the final response.

are arbitrary and can be easily modified. This is a clear advantage of the NRT as it allows for several different modifications, which may facilitate or exacerbate the insight into the underlying regularity. This makes the experimental paradigm very powerful for examining the processes underlying the development of insight. As mentioned, the main advantage of using a task like the NRT is that it enables one to monitor the dynamics of task performance that might reflect the occurrence of an insight.

This is particularly possible because an extremely fast generation of the predictable responses within the NRT indicates that a participant has developed an insight into the underlying regularity. This RT-drop is a clear-cut indicator because the fast computation of the final response cannot be due to a simple retrieval from memory of the final response for the digit string at hand. The digit strings in the NRT are very similar making it impossible to memorize them. In our experiments, no participant was ever able to remember the final response for a given digit string or to remember an entire digit string. Moreover, due to the somewhat complex comparison of the last response and the next digit in the string, it is impossible to predict the final response from simply analyzing the digit string.

A second advantage of the NRT is that due to the underlying regularity, the response strings always contain unpredictable as well as predictable responses. As we show below, the comparison of RTs for predictable and unpredictable responses facilitates the identification of the exact point in time when the insight occurs.

4. Identification of the point in time when the insight occurs

From the above mentioned experiments, we know that in our experiments the ability to verbally describe the underlying regularity (or the insight) corresponds with an RT-drop during training (approximately 95% of the participants who show an RT-drop are also able to describe the underlying regularity). However, if one wants to pursue the dynamics of the processes underlying insight, it may be of particular interest to determine the exact point when the insight starts to develop. Our last section therefore describes a data-analytic strategy of how to determine exactly when in the training the insight starts to develop.

In earlier experiments, we simply defined the point where the RT-drop occurred in the training as that point where the largest mean RT-difference between two successive training blocks occurred. Consequently, we could identify the practice block in which the RT-drop occurred. In principal, one could increase the chronological resolution by averaging across fewer trials. However, this only reduces the timing problem. To illustrate this point, Fig. 2 depicts the mean latencies (averaged over only 10 trials, respectively, instead of over the trials of an entire practice block) for one single participant as a function of training duration and type of input position. Fig. 2 shows the mean RTs for the unpredictable input position 3 and for the predictable input position 5 of the standard version of the NRT.

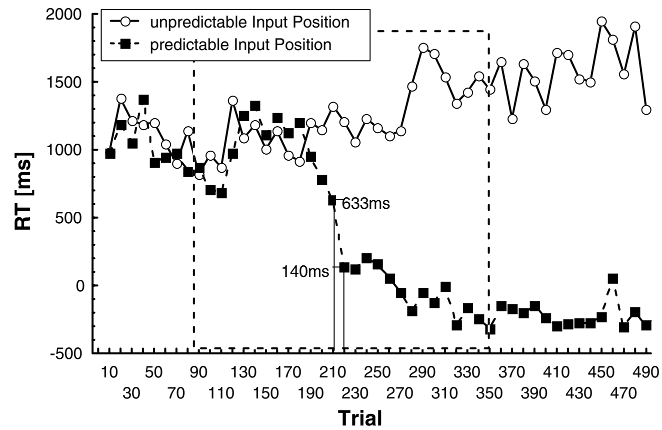

Fig. 2. Mean RTs of unpredictable and predictable input positions as a function of practice blocks (data from one single participant).

As can be seen from Fig. 2, the mean RTs of the predictable input position 5 start to deviate from the mean RTs of the unpredictable input position 3 at around Trial 190. The largest RT-drop (approximately 493 ms) occurs between Trials 210 and 220. According to the above given definition, one would therefore assume that the insight occurs at Trial 220.

However, the mean RTs of the predictable input position already start to deviate at Trial 190. Thus, we cannot know whether the largest RT-difference indeed reflects the starting point of the insight. Furthermore, averaging across 10 trials might attenuate the exact starting point of the RT-drop, as it might start at the end of the last 10 trials (without affecting the mean RT), or it might start exactly with those 10 trials whose mean RT signals the drop.

To eliminate these problems, one can alternatively analyse single trials. However, a clear disadvantage of this approach is that single trial RTs are rather noisy, making it hard to determine exact trends in task performance. To illustrate this point, Fig. 3 depicts the RTs for the unpredictable and the predictable input positions on a trial-by-trial basis (Trials 100 through 300, only). Despite the noise,

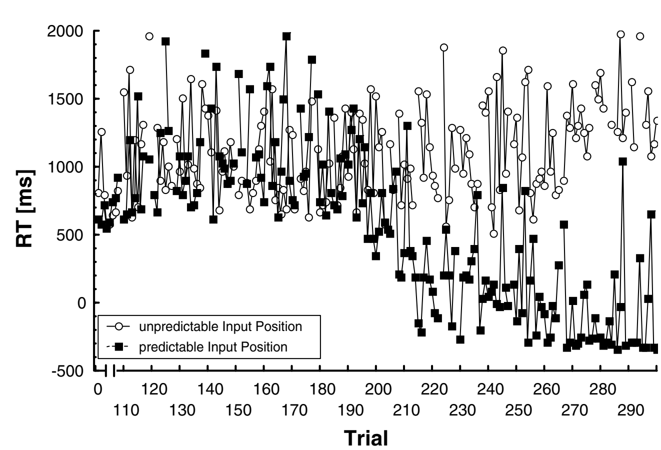

Fig. 3. Single-trial RTs of unpredictable and predictable input positions as a function of trials (Trial 100 trough 300, only).

it becomes obvious that again the RTs of the predictable input position start to deviate from the unpredictable input position at around Trial 190.

In order to get a clearer picture of the trend within single trial RT-data, we incorporated the well established strategy of using a filter algorithm. Usually, moving averages are used for this purpose. However, as the mean RTs, the moving average also smoothes large RT differences, such that it may attenuate the exact point in time when the insight starts to develop. An alternative is to use a median filter [32]. The advantage of this class of nonlinear filters is that it eliminates, as does the moving average, local noise. However, the median filtered data reflect a flat level curve which declines at RT-drops to another flat level curve. With an odd number of points in the median filter, one sees that the output of the median filter will stay up until more than half of the points are on the lower level, whereupon it will drop to the lower level. Thus, the output will follow the discontinuity rather than smoothing out the RT-drop.

For the current analysis, we filtered latencies of the unpredictable and the predictable input positions with a lag-5 median filter, respectively; that is, the first median was computed over Trials 1 through 5, the next median was computed over Trials 2 through 6, and so on. We tried different lags between lag-3 and lag-9. The shorter the lag, the more noise there is in the resulting function. By contrast, increasing the lag decreases sensitivity of the median filter. For our current goal, the lag-5 median filter turned out to be sufficiently sensitive for the RT-drops whilst eliminating enough local noise. The solid lines in Fig. 4 reflect the median filtered latencies of the unpredictable and the predictable input positions. The picture of the single trial RTs now becomes much clearer and as can be seen, the median filtered latencies of the two input positions do not differ up to Trial 195.

In order to determine the exact point at which the RTs of the predictable input position start to reliably deviate from the RTs of the unpredictable input position, we additionally computed a minimum function of the median filtered latencies of the unpredictable input position. The values of this minimum function only change if the actual median of the median filtered latencies is smaller than the last median of the minimum function (in all other cases, the values of this function remain unchanged). Thus, this minimum function describes the lower limit of the response speed for the unpredictable input position. For this function, we then computed a one-tailed confidence interval analogous to confidence intervals for linear regression lines [33]. This confidence interval allowed us to define the starting point of the RT-drop as that point where the median filtered latencies of the predictable input position significantly deviate from the minimum-function of the median filtered latencies of the unpredictable input position. The minimum function and its confidence interval are also shown in Fig. 4 (the two dashed lines). As can be seen from Fig. 4, the median filtered latencies of the predictable input position start to significantly deviate from the median filtered latencies of the unpredictable input position at Trial 207.

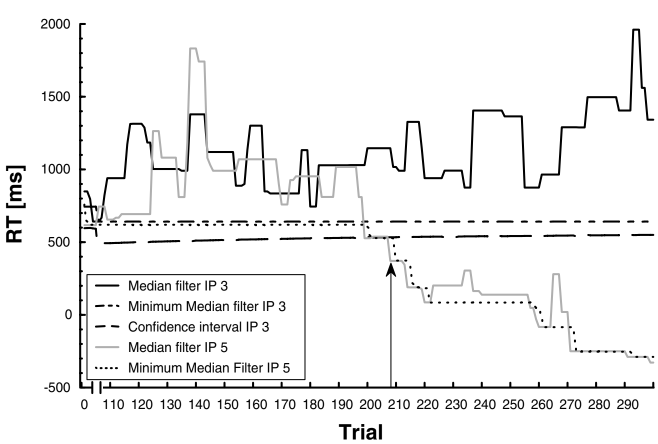

Fig. 4. Median filtered RTs of unpredictable (Ip 3) and predictable (Ip 5) input positions, minimum functions of the median filtered RTs (Ip3 and Ip5) and confidence intervals for the minimum function of the median filtered RTs of input position 3 (Trial 100 through 300).

Thus, the method introduced here can be used to determine the (more or less) exact practice trial representing the onset of the RT-drop. In two behavioral studies, we confirmed that this point corresponds to the point where the ability to verbally describe the underlying regularity emerges [31]. More precisely, results from these studies showed that participants who were interrupted after they had exhibited three responses in succession that were significantly faster than the latencies for the unpredictable input position (according to the above described method) were able to verbally describe the underlying regularity. By contrast, participants who were not interrupted during training (although they produced some fast single responses) were not able to describe the underlying regularity. Thus, taken together the proposed data-analytic strategy is suitable for identifying the exact trial when the insight begins to develop during training.

5. Discussion

We started with the question of how to best investigate the processes of insight. As an answer, we propose the use of an implicit learning paradigm, or more precisely, the NRT. As we have shown, participants' performance reflects the occurrence of an insight during the training. The behavioral data of those participants who are able to verbally describe the regularity built into the task show an abruptly occurring RT-drop. This RT-drop is caused by participants' insight into the underlying regularity. Thus, the experimental task introduced here is well suited for investigating the dynamic development of insight. It is less suited for investigating the impasse-insight sequence. However, a last question that may arise is whether or not other well established implicit learning tasks, such as the serial reaction time task (SRTT, [7]), could also be recruited to study insight.

In the SRTT, participants are seated in front of a computer screen on which e.g., four screen locations are marked. The four locations are mapped individually to four response keys on the computer keyboard. On any trial, a symbol appears at one of the marked locations. A participant's task is simply to press, as fast as possible, the response key corresponding to the location at which the symbol appears. Unbeknownst to the participants, the marked locations on the screen follow a regular sequence; for instance, a sequence of marked positions, such as 1, 4, 2, 3, 2, 4, 1, 3 which is repeated over several trial blocks. Usually, at some point during the training, the sequence is replaced by either a random sequence or a second sequence in order to assess implicit learning. If participants have already acquired implicit knowledge about the regular sequence, RTs usually increase. After the experiment, participants are asked what they know about the underlying regular sequence. As mentioned in the introduction, some participants are able to verbally describe the entire regular sequence after training.

We also conducted several experiments using the SRTT in order to investigate the process of insight within this task (see, [34]). Overall, the findings with the SRTT are rather similar to those found for the NRT; that is, participants who are able to verbally describe the sequence in a post-experimental interview also exhibit an RT-drop during the training. Nevertheless, we shall argue for using the NRT instead of the SRTT because the latter possesses two important disadvantages.

First of all, while the insight within the NRT occurs rather abruptly—more or less in an all-or-none manner—participants in the SRTT often notice that a regular sequence exists, but then need several trials to discover the entire sequence. This is particularly the case when the sequence is longer than six digits. Consequently, in post-experimental interviews some participants are not able to verbally describe the entire sequence, but only parts of it or they mix up digit positions within the sequence, although their performance data indicate a clear RT-drop. Thus, in the SRTT, the correspondence between diagnosed RT-drops and the ability to verbally describe the entire sequence is not as clear as in the case of the NRT.

A second disadvantage of the SRTT concerning the determination of an RT-drop is that participants in this task usually receive several blocks of practice. Each block starts with an arbitrarily determined position within the sequence. Consequently, even when participants explicitly know the sequence, they often need several trials at the beginning of a new block to match the starting point of their explicitly represented sequence within the currently given sequence (e.g., a participant represents the sequence as 14232143, and the sequence in the new block starts with 32143142). This causes an increase in RTs at the beginning of a new block that can remain for several trials. This variability of RTs at the beginning of each block can make it rather difficult to determine the exact point in time where the insight starts, particularly if the insight starts at the end of a block. By contrast, a participant in the NRT who has discovered the underlying regularity normally does not turn back to the old strategy when a new block starts.

Thus, these two disadvantages inherent in the SRTT caused us to choose the NRT. However, one should not dismiss the SRTT, as there may be other research questions for which it is better suited. It is important to note that, in addition to the above mentioned differences, the SRTT and the NRT also differ with regard to the brain activity underlying implicit learning. Implicit learning in the SRTT mainly involves the basal ganglia. By contrast, our fMRI-data revealed that in the NRT, implicit learning activates the ventral perirhinal cortex within the medial temporal lobe and the explicit rule learning (Same- and Different rule) mainly involves the basal ganglia (for further details, [26]). At the moment, we do not know whether or not this different mechanisms underlying implicit learning in the NRT and the SRTT might also affect the processes underlying the development of insight.

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