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Dissociating automatic and controlled processes in a memory-search task: Beyond implicit memory

Abstract Our goal in this paper was to examine the processes that give rise to action slips. Procedures used to examine implicit memory and automatic processes were found to be unsatisfactory. However, the process-dissociation procedure proved useful for examining the contribution of the automatic and controlled processes underlying performance. The procedure was used in conjunction with a Sternberg memory-search task to examine the effects of set size, response speed, and stimulus–response mapping on controlled and automatic processes. The formulation allowed us to predict accurately how subjects would perform in a varied mapping condition. Moreover, set size and response speed were found to influence the controlled search process, but to leave the automatic influences unaffected. Stimulus–response mapping, on the other hand, was found to lead to probability matching in the automatic processes; this pattern was found to remain constant across changes in set size and response speed.

Introduction

William James (1890) observed that "very absent-minded persons in going to their bedroom to dress for dinner have been known to take off one garment after another and finally to get into bed." This "action slip" (Reason, 1979) illustrates how nonintended or automatic influences of memory can interfere with intended actions. It is likely that the act of getting undressed was most often followed by the act of getting into bed, and the action slip of going to bed was a result of automatic influences or of habit formed on these prior occasions dominating over the intended action of dressing for dinner. The goal of our research is to better understand action slips, by separating the automatic influence of memory from the influence of intention. We describe our use of a process-dissociation procedure (Jacoby, 1991; Jacoby, Toth & Yonelinas, 1993) to accomplish this goal. Before doing so, we consider the relation of action slips to implicit memory, and describe other attempts to separate automatic and controlled influences of memory.

The automatic influences responsible for action slips may be the same as the implicit memory that has been the topic of much recent investigation. Implicit memory is defined as memory whose effects are produced without the intention to remember. For a test of implicit memory, people are not asked directly to remember, but rather to engage in a task that can indirectly reflect memory (for reviews, see Richardson-Klavehn & Bjork, 1988; Roediger & McDermott, 1993). Findings of dissociations between performance on implicit and explicit tests are taken as evidence for the existence of separate memory systems or processes underlying the two types of test. As an example of a dissociation, for a stem-completion task (e.g., complete "mot – –" with a word), implicit memory gained from earlier reading a completion word "motel" facilitates performance, even when people are unable to recollect an earlier reading of the word. Action slips can be described as a case for which implicit memory interferes with, rather than facilitates, performance.

However, the research on implicit memory adds little to the understanding of action slips. Most investigations of implicit memory provide very little practice, as in the case of a single presentation of a word being held responsible for implicit memory, whereas the automatic influences responsible for action slips often reflect extensive practice. More importantly, action slips reflect automatic influences that operate in the context of a contradictory intention, and those automatic influences may be different from implicit memory measured in the absence of the intention to remember. The difficulty is that an implicit test cannot be treated as yielding a "process pure" measure of implicit

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memory that maintains its identity across situations (e.g., Jacoby & Kelly, 1992). We return to this problem later.

Some (e.g., Jacoby et al. 1993; Logan, 1990) have suggested that "implicit memory" is synonymous with "automaticity." How do the techniques used to investigate automaticity fare with regard to providing a means for investigating action slips? By the standard definition, automatic processes are those that do not require attentional capacity, do not require intent, are carried out without awareness, and arise when stimulus–response conditions remain constant (Hasher & Zacks, 1979; Logan, 1988; Shiffrin & Schneider, 1977). Schneider and Shiffrin (1977), and Shiffrin and Schneider (1977), used a contrast between consistent and varied mapping to separate automatic and controlled processing. Consistent mapping (CM) refers to tasks in which targets and distracters never exchange roles over trials. Thus stimulus–response mapping remains constant. Varied mapping (VM) refers to tasks in which targets on one trial may be distracters on another, and vice versa. Extended practice in CM, but not in VM tasks, was shown to result in marked flattening of memory set-size functions in memory and visual-search tasks. The claim is that automatic processing arises only under CM conditions, and that VM conditions require controlled search. Thus performances under CM and VM conditions are used as measures of automatic and controlled processes, respectively.

However, the contrast between CM and VM is of little help for separating the contributions of automatic influences responsible for action slips. Action slips are errors produced by an automatic basis for responding. As an example, an action slip would be evidenced by falsely responding "yes" to an item that was not in the memory set because that item in the past had almost always been in the memory set when the subject was tested. The CM and VM conditions used by Shiffrin and Schneider do not allow such action slips to be observed. In the CM condition, which is identified with automaticity, if the item is a target, it always leads to a "yes" response. Thus automaticity always facilitates performance because the intended action should be the same as the automatic action. For the VM condition, the probability of the two responses for a particular item is .5 and, so, any automaticity that does develop would not differentially favour either response.

As a means of investigating action slips, the contrast between CM and VM shares a problem with the contrast between implicit and explicit tests. Both contrasts are an attempt to use a particular test condition to gain a pure measure of automaticity or implicit memory. However, tests of implicit memory are probably sometimes contaminated by the intentional use of memory (e.g., Jacoby, 1991; Richardson-Klavehn & Bjork, 1988). Also, as was acknowledged by Shiffrin, Dumais, and Schneider (1981), conscious memory search often plays a role even in a CM condition. What is needed is some means of separating the contributions of automatic and intentional processing within the confines of a single task. Doing so is the goal of the process-dissociation procedure (e.g., Jacoby, 1991; Jacoby et al., 1993). Our experiments were done to extend that procedure to separate bases for responding in a Sternberg (1966) memory-search task.

The process-dissociation procedure

The process-dissociation procedure measures consciously controlled processes by combining results from a condition for which automatic and controlled processes act in opposition, as in the case of action slips, with results from a condition for which the two processes act in concert. Typically, measures are attained by the examination of performance under two different sets of test instructions (see Jacoby et al., 1993). However, in the current set of experiments we follow Lindsay and Jacoby (1994) in attaining measures by manipulating materials rather than instructions. This strategy has also been used by Jacoby, Jennings, and Hay (in press). It is in the larger context of other work that treating performance in a Sternberg task as a way of studying action slips becomes meaningful.

In our experiments, subjects received extensive practice, over several weeks, performing a memory-search task. On each trial, a short list of consonants was presented as a memory set and followed by presentation of a target item. Subjects were to respond before a response deadline to indicate whether the target item was or was not in the memory set. We used the deadline procedure to ensure that performance was not perfect, so as to allow us to examine action slips. Without the subjects' knowledge, there were three distinct classes of items, each with a different stimulus–response (S–R) mapping. That is, across trials, items differed in the probability of their having been in the memory set when tested. For one class of items, 75% of the time they were presented as a target they had been in the memory set. The corresponding probability for other classes of items were 50% and 25%. This manipulation of probability is analogous to the manipulation of CM vs. VM. For CM, the probability, across trials, of a particular item having been in the memory set when tested is 1.0 for targets and 0.0 for distracters. Avoiding these extreme probabilities let us sort trials into congruent and incongruent trials, and then use the process-dissociation procedure to separate automatic influences and memory search as bases for responding.

Consider the probability of accepting a letter mapped 75% of the time to a "yes" response. When the item was in the memory set (a congruent trial), subjects could correctly respond "yes" either because of a successful controlled search (C), or in the absence of a successful search ($1 - C$), because of automatic influences of memory (A) for previous responses to the item.

Thus:

P ("yes"/old) = C + (1 − C)A

If the target item was not in the memory set, the two bases for responding would be incongruent and an action slip might result. That is, previous habit would lead to a "yes" response, but memory search would lead to a "no" response. Under these conditions a "yes" would occur if the controlled search failed (1 − C) and the subject responded on the basis of the automatic influences (A). Thus:

P("yes"/new) = (1 − C)A

These two equations can be used to estimate the contribution of controlled and automatic processes to overall performance. However, use of the same "C" term in both equations implies that the probability of a successful search is the same for items in the memory set as for items not in the memory set. It is likely that the probability of searching a set and finding an item before a deadline is greater than the probability of determining that an item is not in the memory set. To acknowledge this difference, the equations can be rewritten, with Co representing the probability of finding the target item (an old item) in the memory set, and Cn to represent the probability of finding that the target item was not in the memory set (a new item). This creates the problem of having three unknowns and only two equations. However, we can estimate the contribution of automatic and controlled processes if we also consider performance in the 25% S–R mapping condition. If we assume that automatic influences are different for this class of items, but that the probability of a successful memory search is the same, then we have four equations (hits and false alarms for the 75% and the 25% items) and four parameters (Co, Cn, A75, and A25). Given that situation, we can derive unique solutions for the parameters (see Appendix for algebraic solutions).

But how can we assess these estimates? That is, how do we know that our estimates represent the processes underlying performance correctly? One way to assess the viability of our approach is to use the estimates gained from the 75% and 25% conditions to predict performance in the 50% condition. This is of particular interest because the 50% condition corresponds to the VM condition, which has been identified with controlled processing by Shiffrin and Schneider (1977). Our goal was to separate the contributions of automatic and controlled processes to performance in that condition.

Predicting performance in the VM conditions

As has been described above, performance in the 75% and 25% conditions can be used to estimate Co and Cn for the VM condition. However, how can an estimate of automatic influences for that condition be gained? One possibility is that the magnitude of automatic influences will correspond closely to probability matching (Estes, 1976) so that for the VM condition, the value of A can be estimated as .50. Because the probability that VM items were in the memory set when subjects were tested was .50, we did not expect automatic influences to favor either a "yes" or a "no" response. If our estimates are accurate, the hit rate for the 50% items should be equal to the probability of a correct search (Co) plus the probability that the item was not found (1 − Co) times the probability of responding "yes" on the basis of a guess (.50). The false-alarm rate for these items should be equal to the probability that the search did not lead to a correct "no" response (1 − Cn), times the probability of responding "yes" on the basis of a guess (.50).

In Experiment 1 we examined the effect of varying memory set size (4, 6, or 8) and response deadline (450 vs. 550 ms). This allowed us to assess the match between predicted and observed performance across conditions in set-size and response-deadline conditions. In addition to predicting performance in VM conditions, we used the complete data set to examine the effects of set size, response deadline, and S–R mapping on the controlled and automatic processes that support overall performance. Best-fit estimates were gained for the probability of a successful memory search (Co and Cn) as well as the automatic influences for the three classes of items (A75, A50, and A25). We expected that set size and response deadline would influence the probability of a successful memory search (controlled processes), but would leave automatic influences unchanged. Further, we expected estimates of automatic influences to approximate probability matching. That is, estimates of the probability of a "yes" response on the basis of automatic influences should be close to the objective probability, across trials, of a tested item being in the memory set.

In Experiment 2 we again examined the effects of response speed, but used a response-signal procedure rather than the deadline procedure. The S–R mappings were changed to .20, .40, .60, and .80 to assess further whether probability matching would be obtained.

Experiment 1

Method

Subjects and materials. Six McMaster University graduate students (three males) were paid for their participation in the experiment. All subjects had approximately 6 hours of practice with the materials and procedure before the beginning of the experiment. Prior to this, one of the subjects was tested in several short pilot studies that took approximately 4 hours. Twelve consonants were selected as memory-set items. The items were divided into three sets: F, J, P, V; D, H, Q, T; B, G, R, S. For each subject, each set was assigned to one of three experimental conditions. The sets were rotated in such a way that each item appeared equally often in each condition.

Design and procedure. Materials were presented and responses collected on PC-compatible computers. The character size was approximately 5 × 5 mm and the viewing distance was approximately .5 m. Stimuli were presented in upper-case letters in the centre of the screen. Subjects were tested repeatedly on a memory-search task. Each trial began with the presentation of a memory set consisting either of 4, 6, or 8 letters. When the subjects were ready, they pressed a key and the screen was cleared. After a 1-s delay, a target item was presented and the subject was required to respond by pressing one of two keys. The subjects responded "yes" or "no" by pressing a designated key on the computer keyboard. Half of the subjects responded "yes" with the right hand and "no" with the left. The reverse was true for the remaining subjects. If the subject made an incorrect response, a short tone was sounded by the computer. Moreover, if the response occurred after a set deadline (550 ms after the onset of the target item) an error tone was sounded.

All items appeared equally often as target items, as well as appearing equally often as study times. However, given that a particular item was the target item, the probability that it was in the memory set was varied. Thus the stimulus–response correlations varied. For one set of items, 75% of the time that the item was the target item, it was in the memory set (25% of the time it was not in the set). For a second set of items, 50% of the time that the item was the target, it was in the memory set. For the final set of items, given that the item was the target, there was a 25% probability that it was in the memory set.

Each experimental session consisted of 156 trials (12 practice trials and 144 critical trials) and took between 10 and 20 minutes to complete. The critical trials consisted of 48 trials of each set size, presented in a random order. Subjects completed two blocks of 20 sessions each. Each block consisted of 5 training sessions and 15 critical sessions. For the first and second blocks, the response deadline was 450 and 550 ms respectively. A significance level of .05 was used for all statistical tests.

Results and discussion

Predicting VM performance. The effect of response speed was examined by a comparison of performance under the fast, and under the slow response deadlines. The average hit and false-alarm rates for the 75% and 25% S–R mapping conditions are presented in Table 1. Only responses made before the response deadline were scored. An analysis of variance (ANOVA) was conducted to examine the effect of Response Deadline (fast/slow), S–R mapping (25/75), and Test Condition (old/new) on response accuracy. As can be seen in Table 1, the hit rate was greater than the false-alarm rate, $F(1,5) = 21.27$, $MS_e = .065$, showing that subjects could discriminate between items that were and those that were not in the memory set. Moreover, as the response deadline increased, the ability to discriminate whether or not an item was in the memory set increased. This increase in hit rate and the decrease in the false-alarm rate was reflected by a significant interaction of Deadline with Test Condition, $F\,(1, 5) = 14.695$, $MS_e = .006$.

As the S–R Mapping increased from 25% to 75%, the probability of a "yes" response increased, $F(1,5) = 37.231$, $MS_e = .016$. Moreover, the effect was greater for the false-alarm rate, which increased from .28 to .55, than for the hit rate, which increased from .66 to .84. This was reflected by a significant interaction of S–R Mapping with Test Conditions, $F(1,5) = 100.00$, $MS_e = .0002$. There were no other significant effects (all $Fs < 1$).

Performance in the 75% and 25% conditions was used to predict performance in the VM conditions (50% S–R mapped items). Using the scores in Table 1 and the equations described earlier, we calculated the probability of a successful search (Co and Cn) for each response deadline. Using these values, along with the assumption that the probability of responding "yes" on the basis of automatic influences was .50, we computed estimates for the hit and false-alarm rates for the VM conditions. The predicted and observed hit and false-alarm rates for the VM conditions are presented in Table 2.

Table 1 The proportion of hits and false alarms as a function of response deadline (ms) and S–R mapping for Experiment 1

		P("yes")	
Deadline	S–R Mapping	Old	New
450	25%	.62	.31
	75%	.80	.60
550	25%	.69	.23
	75%	.86	.48

Table 2 Predicted and observed performance on the VM items as a function of response deadline (ms) in Experiment 1

Response Deadline	Hits		False alarms	
	Predicted	Observed	Predicted	Observed
450	.71	.70	.46	.46
550	.77	.77	.34	.32

An examination of Table 2 shows that the predicted hit and false-alarm rates for the VM conditions were almost identical to the observed values. The average predicted hit rate was equal to the average observed hit rate (.74). The average predicted false-alarm rate was .40 compared to the observed false-alarm rate of .39. The fit between predicted and observed levels of performance shows the viability of our approach.

In an additional analysis the effect of set size was examined. Table 3 presents the proportion of hits and false alarms for the three set sizes (4, 6, and 8) across the two S–R mapping conditions (75, and 25) for the final block.[1] The hit rate was greater than the false-alarm rate, $F(1,5) = 20.867$, $MS_e = .155$. Moreover, as the set size increased, the hit rate decreased and the false-alarm rate increased, resulting in a significant

[1]The analysis was based on data from the final block, because examination of the individual scores in the first block suggested that in the larger set size, some subjects were exhibiting very poor performance and may have been responding randomly

Table 3 The proportion of hits and false-alarms as a function of set size and stimulus–response mapping for Experiment 1

		P("yes")	
Set size	S–R Mapping	Old	New
4	25%	.72	.15
	75%	.90	.35
6	25%	.70	.23
	75%	.87	.50
8	25%	.65	.32
	75%	.83	.58

Table 4 Predicted and observed performance on the VM items as a function of set size in Experiment 1

	Hits		False alarms	
Set Size	Predicted	Observed	Predicted	Observed
4	.79	.82	.23	.21
6	.78	.74	.35	.32
8	.71	.76	.41	.43

interaction of Set Size with Test Conditions, $F(2,10) = 63.444$, $MS_e = .002$.

The probability of responding "yes" was higher in the 75% than in the 25% condition, $F(1,5) = 20.614$, $MS_e = .038$. However, the effect was slightly greater for the false-alarm rate, which increased from .23 to .48, than for the hit rate, which increased from .69 to .86. This was reflected by a significant interaction of Mapping with Test Conditions, $F(1,5) = 12.444$, $MS_e = .002$. There were no other significant effects.

Performance in the 75% and 25% conditions was used to predict performance in the VM conditions (50% S–R mapped conditions). Estimates of Co and Cn were gained for each of the memory set sizes and used to predict hit and false-alarm rates for the VM conditions. The hit and false-alarm rates that were predicted and observed are presented in Table 4.

Examination of the data in Table 4 shows that, as in the previous analysis, the predicted hit and false-alarm rates for the VM items were close to the values observed. The average predicted hit rate was .76 compared to the average observed hit rate of .77. The average predicted false-alarm rate was .33 compared to the observed false alarm rate of .32. The deviations from the scores predicted were slightly greater for memory set size than for response deadline. This is not surprising, as the estimates of Co and Cn used to compute predicted values are based on 1/3 of the number of observations per condition as used to predict effects of response deadline.

The analysis showed that the process-dissociation procedure allowed us to use performance on the 75% and 25% items to predict performance in the VM items. The close fit between predicted and observed performance on those items strongly suggests that the formulation underlying that analysis is valid. Having found support for the general procedure, we proceeded further to use the procedure to examine the effect of response deadline and set size on the automatic and controlled processes.

Table 5 Parameter estimates for the controlled search processes as a function of response deadline (ms) in Experiment 1

	Parameter Estimates	
Deadline	Co	Cn
450	.41	.09
550	.59	.32

Parameter estimation

Response speed. An analysis was conducted, with performance on all three classes of S–R mapped items, to determine the effects of response speed and S–R mapping on the automatic and controlled processes. A best-fit procedure was used to derive estimates for memory search (Co and Cn) and guessing (A25, A50, and A75). Estimates were gained by the simultaneous solving of equations for the three types of items (25%, 50%, and 75%). For each deadline we had two equations (hits and false alarms) for each type of item (25%, 50%, 75%). Thus we had six equations and five unknowns (Co, Cn, A25, A50, and A75). Estimates were derived separately for each response deadline for each subject. We used a gradient descent-search algorithm to find the best-fit solution by minimizing the sum of the squared errors. Parameter estimates with the best-fit solution were found to approximate closely those derived algebraically in the previous analysis.

The average parameter estimates for the controlled-search process are presented in Table 5. An ANOVA showed that response deadline influenced the controlled processes. As response time increased, the C parameters increased, $F(1,5) = 26.537$, $MS_e = .010$, showing that an increase in the available search time increased the probability of a successful search. Moreover, Co was greater than Cn, $F(1,5) = 14.798$, $MS_e = .034$, showing that the probability of correctly finding that an item was in the memory set was greater than the probability of correctly finding that an item was not in the memory set. Collapsed across deadlines, the estimates for Co and Cn were .53 and .34 respectively. The interaction of Deadline with Test Conditions was not significant ($F < 1$).

An analysis was also conducted on the parameter estimates for the automatic processes. The automatic parameters were not significantly influenced by the response deadline, $F(1,5) = 2.250$, $MS_e = .004$. Collapsed

Table 6 Parameter estimates for the controlled search processes as a function of set size in Experiment 1

Set Size	Parameter Estimates	
	Co	Cn
4	.60	.56
6	.56	.30
8	.54	.10

across S–R mapping, the estimates for guessing were .50, and .46, for fast and slow deadlines respectively. However, guessing was influenced by the S–R mapping, $F(2,10) = 34.963$, $MS_e = .011$. Collapsed across deadlines, the estimates for guessing were .32, .46, and, .67, corresponding to S–R mappings of 25%, 50%, and 75%. These estimates approximate probability matching with some "pinching in" at the extremes, as would be expected if responding were sometimes random. The interaction of Response Deadline with S–R Mapping was not significant, $F(2,10) = 1.344$, $MS_e = .003$.

Set size. A further analysis was conducted to determine the effects of set size and S–R mapping on the automatic and controlled processes. Estimates for memory search and guessing were derived in the same way as in the previous analysis, and are presented in Table 4. Examination of Table 4 shows that set size influenced the controlled search process. As set size increased, the search parameters decreased, $F(2,10) = 6.248$, $MS_e = .033$, showing that memory set size influenced the controlled search process. Moreover, as in the previous analysis, the estimates for Co were slightly greater than those for Cn, suggesting that the probability of correctly detecting an item in the search set was greater than the probability of detecting that an item was absent from the search set. However, unlike in the previous analysis, the difference failed to reach statistical significance, $F(1,5) = 4.243$, $MS_e = .123$. Presumably, this reflects the fact that the estimates were based on 1/3 of the number of observations. Finally, the interaction of Set Size with Test Conditions approached, but did not attain, significance, $F(2,10) = 3.125$, $MS_e = .039$. The advantage of Co over Cn tended to be greater for larger memory set sizes.

An analysis conducted on the parameter estimates of the automatic processes showed that set size did not influence the automatic processes significantly ($F < 1$). Collapsed across the S–R mappings, the estimates for guessing were .55, .47, and .49, for set sizes 4, 6, and 8 respectively. However, S–R mapping did influence the automaticity parameter, $F(2,10) = 34.102$, $MS_e = .021$. Collapsed across set size, the estimates were .33, .47, and .72, corresponding to S–R mappings of 25%, 50%, and 75%. The interaction of Set Size with S–R Mapping was not significant, $F(4,20) = 1.576$, $MS_e = .007$.

The results of the parameter analysis were generally as expected. Both response speed and set size influenced the controlled, but not the automatic, process. The increase of response deadline, as well as that of memory set size, led to a decrease in the probability of a successful memory search. Furthermore, S–R mapping was found to influence the automatic process systematically, so that the probability of guessing "yes" closely approximated the objective stimulus–response probability. The parameter estimates for Co were greater than those for Cn, suggesting that our decision to represent them as different parameters was well founded. Although the difference failed to reach significance in the set-size analysis, it did reach significance in the deadline analysis, where the statistical power was greater.

Experiment 2

In Experiment 1, the effect of time for responding was examined by comparison of performance in two blocks of trials, with response deadline varied across the blocks. However, in so doing, we confounded response speed with the amount of practice that the subjects had had. Although all of the subjects had received extensive practice even before the first block of trials, it is possible that the difference we observed across blocks was due, in part, to the effects of practice. In Experiment 2, time for responding was mixed randomly within each session to avoid any confounding with practice effects. The procedure was similar to that of Experiment 1, except that a response-signal procedure was used rather than a deadline procedure. A response signal was sounded either 150 or 300 ms after the target item had been presented, and subjects were required to respond immediately upon hearing the response signal. Each session contained a random mixture of fast and slow response-signal trials, such that subjects were equally practiced at both response speeds. There were two other minor changes to the procedure. First, memory set size was fixed at six items for every trial. Second, there were four, rather than three, different S–R mappings (20%, 40%, 60%, and 80%). Because we did not include a 50% S–R mapping condition, we could not test predictions about VM performance. However, as in the previous experiment, we did use the process-dissociation procedure to examine the effects of speed of response on the automatic and controlled processes underlying performance.

Method

Subjects. Four McMaster University graduate students (one male) were paid for their participation in the experiment. None of the subjects had participated in Experiment 1. However, they had completed a number of training sessions and were familiar with the materials and procedure.

Material, design, and procedure. These were the same as in Experiment 1 with the following changes. A response-signal procedure was used, and so shortly after the presentation of the target item a response signal was sounded. The signal was presented either 150 (fast) or 300 ms (slow) after the presentation of the target. The fast and slow test trials were presented in a random order, so that subjects did not know how long they had to search on any particular trial until they heard the response signal. An error message appeared if subjects responded before the response signal ("too fast") or later than 300 ms after the signal ("too slow"). The memory set size was fixed at six items. There were four different classes of items, containing four items each. The S–R mappings for the four classes of items were 20%, 40%, 60%, and 80%.

Each subject completed 28 sessions. Each session took between 10 and 15 min, and contained 12 practice trials followed by 160 critical trials. The critical trials contained 40 trials of each class of item as a target item, mixed in a random order.

Results and discussion

The effect of search time was examined by comparison of performance on fast and slow response-signal trials. Only responses made between 0 and 300 ms after the response signal were scored. A subsequent analysis showed that the score of all responses did not change the pattern of results. Table 7 presents the proportion of hits and false alarms for the 150-ms and the 350-ms response-signal trials across the four levels of S–R mapping (20%, 40%, 60%, and 80%). As in the previous experiment, the hit rate was greater than the false-alarm rate, $F(1,3) = 2201.818$, $MS_e = .009$. Moreover, the ability to discriminate whether an item was in the memory set increased as search time increased. That is, there was an increase in hit rate and a decrease in the false-alarm rate, which was reflected by a significant Response Signal by Test-Condition interaction, $F(1,3) = 11.304$, $MS_e = .002$. As the S–R mapping increased, the probability of accepting items increased, $F(3, 9) = 66.429$, $MS_e = .005$. Although the effect was slightly greater for the false-alarm rate, which increased from .17 to .52, than for the hit rate, which increased from .52 to .82, it did not result in a significant S–R Mapping by Test-Condition interaction, $F(3,9) = 1.339$, $MS_e = .002$. There were no other significant effects (all Fs < 1).

Parameter estimates for Co, Cn, A20, A40, A60, and A80 were derived as in the previous experiment. The average parameter estimates for the controlled search process are presented in Table 8, examination of which shows that as response time increased, the search parameters increased, $F(1,3) = 17.526$, $MS_e = .002$, showing that the probability of a successful memory search was influenced by the search time available. Although, Co was greater than Cn under fast and slow response-signal conditions, the difference was not significant, $F(1,3) = 1.798$, $MS_e = .033$. The average estimates for Co and Cn were .40 and .28 respectively. Although the difference tended to be larger for fast responding, the interaction of Response Signal and Test Conditions was not significant, $F(1,3) = 2.468$, $MS_e = .005$.

Table 7 The proportion of hits and false alarms as a function of response signal (ms) and S–R mapping in Experiment 2

		P("yes")	
Response Signal	S–R Mapping	Old	New
	20%	.52	.20
150	40%	.58	.29
	60%	.69	.37
	80%	.79	.54
	20%	.52	.14
300	40%	.62	.24
	60%	.72	.33
	80%	.84	.49

Table 8 Parameter estimates for the controlled search processes as a function of response signal (ms) in Experiment 2

	Parameter Estimates	
Response Signal	Co	Cn
150	.38	.20
300	.41	.35

An analysis of the guessing parameters showed that time for responding did not significantly affect automatic processes ($F < 1$). Collapsed across S–R mapping, the estimates for automaticity were .43 and .45 for fast and slow response-signal conditions respectively. However, as in the previous experiment, the S–R mapping did influence automaticity, $F(3,9) = 59.317$, $MS_e = .006$. Collapsed across deadline, the estimates for automaticity were .21, .35, .49, and .71, corresponding to S–R mappings of 20%, 40%, 60%, and 80% respectively.

The results of Experiment 2 are in agreement with those of Experiment 1. Response speed was found to influence the controlled search processes, but not to influence the automatic basis for responding. S–R mapping was found to influence the automatic processes in the form of probability matching for both fast- and slow-response conditions. Co was slightly greater than Cn, but the difference did not reach significance.

This last result may lead to worries that, with only four subjects, we lacked statistical power. But the number of observations per subject and condition was large, and there was sufficient power to reveal some highly significant effects. None the less, caution may be warranted in the interpretation of those effects that fell slightly short of significance, such as the example just mentioned, comparing Co and Cn. However, because the difference was significant in the previous experiment, it seems likely that with more subjects a difference between Co and Cn would have been detected. In any case, we feel that our decision to represent Co and Cn as different parameters was not entirely unfounded.

Would a larger number of subjects influence the conclusions about the effects of set size and response time upon the automatic processes? It seems unlikely. In the current experiment, the estimate for A decreased by .02 for the fast responses, compared to the slow responses. However, in Experiment 1 A increased by .04 for fast responses, compared to slow responses. Similarly, in Experiment 1, increasing set size had no consistent effect on A, and the effect did not approach significance ($F < 1$).

General discussion

For the understanding of action slips, use of the process-dissociation procedure allowed us to go beyond any understanding that could be gained by means of those procedures employed to investigate implicit memory. One problem with implicit tests is that subjects may sometimes catch on to the purpose of the implicit test and change their basis for responding, with the result that performance on the implicit test is contaminated by consciously controlled processes (e.g., Jacoby, 1991; Richardson-Klavehn & Bjork, 1988). A more important problem with identifying automatic or nonintentional influences with performance on an implicit test is that a process may be qualitatively different across tasks (e.g., Jacoby & Kelley, 1992). The issue here is something like the issue of whether people express what they truly believe when drunk. It is possible that what people believe when drunk is qualitatively different from what they believe when sober. Similarly, the nonintentional influences that operate to produce an action slip in the presence of a contradictory intention may be qualitatively different from those revealed by an implicit test.

The procedures used to examine automaticity share the same problems. The use of CM and VM test conditions to examine automatic and controlled processes also reflects the attempt to find process pure measures. Although automaticity is said to arise under conditions of consistent mapping, it is unlikely that this serves as a satisfactory definition of automaticity, because performance in those conditions reflects a combination of automatic, as well as of controlled, processing. Furthermore, like pure implicit tests, the automatic processes under CM conditions may not provide a measure of automatic processes in the presence of a contradictory intention, as in the case of action slips.

By use of the process-dissociation procedure, we solve these problems by separating the contributions of automatic and controlled processes within performance of the task that is of interest. Comparison of performance in facilitation and interference conditions allows us to examine the contribution of automatic and controlled processes across a range of S–R mapping conditions. In contrast to defining automaticity in terms of the type of memory instructions or of the mapping between stimulus and response, we define automaticity solely in terms of the relation between performance in a facilitation condition and an interference condition. Automatic processes are defined as remaining the same, regardless of whether they facilitate performance or interfere with performance, as in the case of action slips. This allowed us to change conditions, such as consistent mapping and varied mapping, from definitional for automaticity, to variables whose effect we could measure.

The independence assumption

In the current study, we made the strong assumption that automatic and controlled processes operated independently. In support of that assumption, we found that the formulation allowed us accurately to predict performance in the VM conditions across changes in set size and response deadline. Further support for the independence assumption was derived from the experimental dissociations observed. If the two processes are independent, it should be possible to find variables that influence one process, but leave the other in place. Changes in set size and response speed were found to influence the controlled-search process, but to leave the automatic process in place. In contrast, S–R mapping was found to influence the automatic processes in a manner expected by probability matching. This pattern was found to remain constant across changes in set size and response speed.

These results converge with results using the process-dissociation procedure in a number of related domains. We have found that variables associated with automaticity tend to influence the consciously controlled processes, but do not influence the automatic or unconscious processes. So, for example, in recognition memory we find that the speeding of responses as well as the increasing of memory load (list length) reduces the conscious uses of memory, but has little effect on the unconscious influences of memory (Yonelinas & Jacoby, in press). Moreover, in recognition, as well as in stem-completion performance, division of attention has the effect of reducing conscious recollection, but not of influencing the unconscious uses of memory (Jacoby, 1991; Jacoby et al., 1993). More recent work, examining receiver-operating characteristics in recognition memory, suggests that although conscious recollection is all or none, the automatic influence of memory reflects a signal-detection process (Yonelinas, 1994). A question for further research is whether controlled and automatic processes in general can be described in a similar manner.

Theories of action slips

The evidence suggesting that the automatic and controlled processes that underlie action slips are independent does not sit well with current theories of action slips, but does provide support for memory-based models of automaticity. Norman and Shallice (1986) have argued that action slips arise when a "Supervisory Attentional System" fails to modulate the activation of automatic sensory-motor schemata correctly. They argue that action sequences are controlled by sensory-motor schemata, which are triggered when the appropriate conditions are met. However, because many different schemata may have similar triggering conditions, a supervisory attention system is required to modulate behavior by activating or inhibiting particular schemata. If this system is overburdened or unavailable for some reason, then sensory-motor schemata may run off unchecked, leading to a non-intended action. If the control process acts to prime or inhibit automatic sensory-motor schemata, as they suggest, then one would not expect automatic or controlled processes to act independently, as they did in our study.

An alternative approach, which accounts for the observed independence quite naturally is one based on an instance theory of memory (Hintzman, 1976; Jacoby & Brooks, 1984). An instance-based theory has been applied to automaticity by Logan (1988), who argued that controlled processing reflects the operation of a computational algorithm and that automatic processing reflects the retrieval of memories for previous trials. In our study, the controlled search process reflects the operation of the computational algorithm, and the automatic process reflects the product of a separate unconscious memory-retrieval process. Because these two processes operate independently, one would expect to find variables that influence the two processes differently, as was found in our studies. Moreover, if the unconscious retrieval process was based on retrieval of earlier instances, one may expect guessing to match the objective S–R probabilities closely, as was found in our experiments.

One important difference between our studies and much of the work examining automaticity, including that of Logan (1988), is that we used measures of accuracy rather than of reaction time. One of the advantages of measuring accuracy was that it allowed us to uncover the relationship between automaticity and probability matching. A topic for further research is the examination of the relationship between accuracy and reaction-time measures of automatic and controlled processes.

Probability learning as implicit knowledge

The probability matching (cf. Estes, 1976) found for the guessing process would seem to qualify as implicit learning (cf. Reber, 1989). The probability of guessing "yes" closely approximated the objective probability across trials of a tested item being in the memory set, showing that subjects were sensitive to the S–R mappings. However, one could argue that the guessing process observed in our study did not reflect automatic or implicit processes, but rather reflected conscious strategic processes, whereby subjects became aware of the S–R mapping and used this as a basis for responding. However, there are a number of reasons for suspecting that this was not the case. First, informal questioning of subjects at the completion of the experiments suggested that they did not have explicit knowledge of the relationship between stimulus and response. Even if subjects were aware of the precise S–R mappings, it seems unlikely that they could have controlled responding in a way that our estimates of guessing would so closely approximate the objective probabilities. Finally, if guessing were mediated by conscious awareness, we would expect variables that influence consciously controlled processes to influence guessing. The fact that decreasing response time and increasing memory load did not influence the guessing estimates suggests that guessing was not consciously mediated.

Conclusions

The action slip described by James (1890) arose because the habitual action (going to bed) and the intended action (dressing for dinner) were incongruent. Thus the habit interfered with the action intended and led to an action error. However, habits and intention are often congruent, and thus habits facilitate performance. For example, had the intention been to go to bed, rather than to dress for dinner, we would expect the habit of going to bed to have facilitated performance of that action. By comparing performance in congruent and incongruent conditions, we used the process-dissociation procedure, to separate the contributions of automatic and controlled processes to both intended and nonintended actions. By doing so, we went beyond investigations not only of implicit memory, but also those of automaticity. Our procedure allows us to separate the contribution of automaticity within a task of interest rather than identifying automaticity with some particular set of conditions or type of instructions.

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Appendix

75% items:

$P(\text{"yes"}/\text{old}) = H = Co + (1 - Co)A$

$P(\text{"yes"}/\text{new}) = F = (1 - Cn)A$

25% items:

$P(\text{"yes"}/\text{old}) = H' = Co + (1 - Co)A'$

$P(\text{"yes"}/\text{new}) = F' = (1 - Cn)A'$

$A' = ((H - H')/(1 - H'))/((F/F') - (1 - H)/(1 - H'))$

$A = A'(F/F')$

$Co = (H' - A')/(1 - A')$

$Cn = 1 - (F'/A')$