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Item-to-Item Associations in Typing: Evidence From Spin List Sequence Learning

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Associations are formed among the items in a sequence over the course of learning, but these item-to-item associations are not sufficient to reproduce the order of the sequence (Lashley, 1951). Contemporary theories of serial order tend to omit these associations entirely. The current paper investigates whether item-to-item associations play a role in serial order, specifically focusing on whether these associations influence how typists order their keystrokes. To address this question, participants completed variants of the spin list learning procedure (Ebenholtz, 1963). In these experiments, participants practiced typing nonword anagram sequences, and the order of the letters between anagrams was manipulated. Between half of the anagram sequences, both absolute and relative letter order were made inconsistent by scrambling the letters according to a balanced Latin square. For the other half, the letters were instead spun, making absolute order inconsistent but keeping relative order consistent. Learning was faster for anagram sequences with consistent relative order (Experiment 1). Practice on spun sequences with consistent relative order transferred to unpracticed sequences with the same relative order (Experiment 2). Transfer to unpracticed sequences did not depend on the absolute position of the letters in the unpracticed sequences (Experiment 3). However, transfer disappeared if letter order was reversed (Experiment 4). These results suggest that typing does make use of item-to-item associations, at least when associative interference is minimized. Although not sufficient, item-to-item associations are a necessary component of serial order in typing.

Keywords: serial order, typing, sequence learning, item-to-item associations

It has long been postulated that items presented nearby in time become associated with one another (Ebbinghaus, 1885). The formation of these item-to-item associations seems to be automatic and obligatory, forming even when it is not beneficial to do so (Kahana, 2012, p. 126). The earliest theories of serial order appealed to these associations, asserting that order is achieved by traversing the chain of associations between items. In these associative chaining theories, each item is used as a cue to evoke retrieval of the item that followed it in the sequence. In most tasks that require correct serial order, such as typing and speech, there is a small set of items that can compose a sequence (26 letters and roughly 40 phonemes in the English language), but these items are recombined into a multitude of different sequences. Each item is followed by—and therefore associated with—many other items, presumably causing interference among the associations. Also, in rapid sequential skills like typing, sensory transmission times exceed the time taken to transition between responses. From these facets of skilled performance, Lashley (1951) argued that item-to-item associations could not support serial order.

Theories that rely solely on item-to-item associations to achieve serial order (e.g., Murdock, 1995; Solway, Murdock, & Kahana, 2012) have lost support, and many contemporary theories of serial order assume associations between items and their sequence position (position-to-item associations) in lieu of item-to-item associations (for a review, see Hurlstone, Hitch, & Baddeley, 2014). The exclusion of item-to-item associations from contemporary theories raises the question: Do item-to-item associations play any role in serial order? We address this question in the domain of typing, asking whether item-to-item associations influence how typists order their keystrokes.

Typing is a skill in which proper serial order is of clear and paramount importance: typing a word requires the execution of multiple keystrokes in their correct order. In spite of this, comparatively little research has investigated how typists accomplish serial order. There are several theoretical accounts of typing (e.g., Logan & Crump, 2011; MacNeilage, 1964; Salthouse, 1986; Sternberg, Monsell, Knoll, & Wright, 1978), but few formally describe the mechanisms that produce ordered keystrokes. Notable examples are Rumelhart and Norman's (1982) and Logan's (in press) theories of typing, which describe serial order explicitly in computational models. In Rumelhart and Norman's (1982) model, serial order is achieved by a competitive queuing mechanism in which each letter inhibits the letters that follow it in the sequence, producing a gradient of activation that favors early, previously

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unexecuted keystrokes in the sequence (cf. Bryden, 1967; Estes, 1972). In Logan's (in press) model, serial order is controlled by a contextual matching process, in which keystrokes build up a representation of context that is used to retrieve the next letter in the sequence (cf. Howard & Kahana, 2002; Polyn, Norman, & Kahana, 2009). Neither model includes associations between the letters in the word, yet both are capable of producing the patterns of errors seen in typing. Thus, typing—as we currently understand it—does not seem to make use of item-to-item associations.

In spite of these modeling efforts, there is empirical evidence that is consistent with the use of item-to-item associations in typing. For example, the transition time between a pair of letters (the interkeystroke interval; IKSI) is shorter for letters that appear together more frequently in text (Grudin & Larochelle, 1982; Salthouse, 1984). This bigram frequency effect appears in both words and "wordlike" sequences, suggesting that their source is independent of any word-level hierarchical processes that occur in typing (Behmer & Crump, 2017; Grudin & Larochelle, 1982). Letters that appear together more frequently should be more strongly associated with one another. The shorter IKSI for high frequency bigrams aligns with these stronger associations, suggesting that they might be used in typing. However, the same bigram frequency effect could be obtained in the absence of associations between the letters. Letters that are paired together consistently may be represented hierarchically as a chunk. Hierarchical representation would allow these pairs to be typed more automatically and effortlessly than letters that are paired inconsistently. We require more direct evidence than the bigram frequency effect to rule that item-to-item associations play a role in typing.

The Current Study

The goal of the current study was to obtain this evidence. Following similar studies by Yamaguchi and Logan (2014a, 2014b, 2016), we pushed typists back on the learning curve by having them type nonword sequences (e.g., *tpgubk*). Nonword sequences selectively disable well-learned associations between words and letters. The associations that typists have learned between letters, keys, and finger movements remain intact, however. By having each typist practice nonword sequences multiple times, we can observe how knowledge about the sequences develops in isolation from knowledge about key and finger locations. By manipulating the nonword sequences, we can infer what information comprises the sequence-level knowledge used by a skilled typist.

Each nonword sequence was an anagram of another sequence, sharing the same letters but in a different order. We manipulated consistencies in the ordering of the letters between these anagram nonword sequences. For some of the anagrams, we scrambled the letter order using a balanced Latin square. This removed all ordering consistencies between anagram sequences: each letter was presented in each position, and each letter was preceded by and followed by every other letter. For other anagrams, we instead spun the letters between sequences, shifting the absolute position of each letter but maintaining their relative order (e.g., *tpgubk* and *ktpgub*). Practice on a sequence might strengthen item-to-item associations and position-to-item associations. For Latin square anagrams, these associations might serve as sources of interference because each letter would be associated with each position and each other letter. For spun anagrams, position-to-item associations might also serve as a source of interference. However, because relative order is consistent in spun anagrams, each letter pair receives additional practice, and each letter is followed by only one other letter. Consequently, in spun anagrams item-to-item associations have greater opportunity to strengthen and should not interfere with one another. If typing makes use of item-to-item associations, then we should see greater improvement in typing performance on spun anagrams than on Latin square anagrams.

The method of spinning a sequence to make absolute position inconsistent while preserving relative position was pioneered by Ebenholtz (1963). Ebenholtz sought to demonstrate that position-to-item associations play a role in serial learning by comparing learning on spun sequences of items to unspun sequences. He argued that if position-to-item associations play a role in serial learning, then making absolute position inconsistent should affect the rate of learning. This is precisely what he found: Spun sequences were learned more slowly than unspun sequences. Our experimental design is similar to that of Ebenholtz, but our baseline comparison differs. Whereas he used unspun sequences, in which absolute and relative position were consistent, we used scrambled sequences, in which neither absolute nor relative position were consistent. Compared with spun sequences, scrambled sequences lack relative positional consistency. Slower learning on these sequences would demonstrate that typing is sensitive to relative order consistency, consistent with the use of item-to-item associations.

Experiment 1

In Experiment 1, we compared learning on spun anagram sequences, in which absolute order was inconsistent and relative order was consistent between sequences, to learning on Latin square scrambled anagram sequences, in which both absolute and relative order were inconsistent between sequences. Greater improvement—that is, higher accuracy or faster typing speed—for spun anagrams compared with Latin square anagrams is consistent with item-to-item associations playing a role in typing.

Method

Participants. In accord with previous studies examining practice effects on the typing of nonword strings (e.g., Yamaguchi & Logan, 2016), we tested 24 participants. The participants were native English speakers between the ages of 18 and 35 who reported normal or corrected-to-normal vision. Participants had 10.29 years of typing experience on average, and all had formal typing training. Prior to beginning the experiment, participants typed a paragraph about Border Collies, and from this we obtained estimates of their typing accuracy and speed (Logan & Zbrodoff, 1998). On average, 93.78% of their words were typed without error, and they typed at a rate of 74.48 words per minute. The participants were tested in 1 hr timeslots and received $12 or course credit as compensation.

Apparatus and stimuli. We used E-prime 2.0 (Psychology Software Tools, 2012) to present stimuli and record responses. The task was administered on ASUS M32BF desktop computers with BenQ XL2411Z flat screen monitors. Responses were taken from standard QWERTY keyboards. Only the letter keys and spacebar were enabled for the task. The same apparatus was used for all the present experiments.

The stimuli were 6-letter nonwords. There were 4 sets of 6 stimuli. Each stimulus in a set was composed of the same letters in a different order. The letters used in each stimulus set were chosen randomly without replacement. We excluded the letters 'a' and 'e' from selection to reduce the chance of generating word-like nonwords.

For two of the stimulus sets, henceforth called spin list sequences, sequences were constructed by spinning the letters like Ebenholtz (1963). For the other two stimulus sets, called Latin square sequences, sequences were constructed by scrambling the letters according to a balanced Latin square. Scrambling the letters in this manner ensured that there were no consistencies in absolute or relative order between sequences in the same set. Each half of the experiment contained one set of spin list sequences and one set of Latin square sequences. Table 1 illustrates how the stimuli were constructed.

Procedure. All experiments were approved by the Vanderbilt University Institutional Review Board. We obtained written consent from the participants. Before beginning the experiment, we informed the participants about the task: that they would see a string of letters on each trial that they should type exactly as presented, that they should type the string as quickly and accurately as possible, that they should press the spacebar after typing each letter string, and that the backspace key was disabled. Each trial began with a centrally presented fixation cross. After 500ms, the fixation cross was removed and a nonword was presented in its place. The entire sequence was presented simultaneously, and it persisted while participants typed it. The participants' keystrokes were echoed on the screen as they typed the presented string. Pressing the spacebar cleared the screen and initiated the next trial. The same instructions and trial structure were used in all the present experiments.

In the first half of the experiment, participants saw the same 12 stimuli (6 spin list and 6 control) repeated 40 times each for a total of 480 trials. The presentations were blocked by number of repetitions; no sequence could be presented a second time before each sequence was presented once. Within a block of repetitions, each of the 12 stimuli was selected randomly without replacement. In the second half of the experiment, they did the same task with the other two sets of stimuli. They were not explicitly informed of the switch. Participants completed an additional 480 trials using the new stimulus sets. Each participant completed a total of 960 trials. Breaks were provided every 240 trials. These breaks were self-paced, during which participants were permitted to stand up, walk around the room, or briefly leave to use the restroom or get water.

Table 1
Construction of Letter Sequences in Experiment 1

Spin list set							Latin square set						
First half							First half						
Item 1	*t*	*p*	*g*	*u*	*b*	*k*	Item 7	*q*	*f*	*w*	*m*	*s*	*l*
Item 2	*p*	*g*	*u*	*b*	*k*	*t*	Item 8	*f*	*m*	*q*	*l*	*w*	*s*
Item 3	*g*	*u*	*b*	*k*	*t*	*p*	Item 9	*m*	*l*	*f*	*s*	*q*	*w*
Item 4	*u*	*b*	*k*	*t*	*p*	*g*	Item 10	*l*	*s*	*m*	*w*	*f*	*q*
Item 5	*b*	*k*	*t*	*p*	*g*	*u*	Item 11	*s*	*w*	*l*	*q*	*m*	*f*
Item 6	*k*	*t*	*p*	*g*	*u*	*b*	Item 12	*w*	*q*	*s*	*f*	*l*	*m*
Second half							Second half						
Item 1	*y*	*z*	*c*	*n*	*r*	*d*	Item 7	*x*	*h*	*o*	*i*	*j*	*v*
Item 2	*z*	*c*	*n*	*r*	*d*	*y*	Item 8	*h*	*i*	*x*	*v*	*o*	*j*
Item 3	*c*	*n*	*r*	*d*	*y*	*z*	Item 9	*i*	*v*	*h*	*j*	*x*	*o*
Item 4	*n*	*r*	*d*	*y*	*z*	*c*	Item 10	*v*	*j*	*i*	*o*	*h*	*x*
Item 5	*r*	*d*	*y*	*z*	*c*	*n*	Item 11	*j*	*o*	*v*	*x*	*i*	*h*
Item 6	*d*	*y*	*z*	*c*	*n*	*r*	Item 12	*o*	*x*	*j*	*h*	*v*	*i*

Note. These letters serve as examples. Each participant received a different random selection of letters. When presented on the computer screen, the spaces between letters were removed.

Results and Discussion

To assess learning in each sequence type, we analyzed the change in the percentage of trials on which at least one erroneous keystroke was made (error rate), time taken to type the first sequence letter (response time; RT), and time taken to type letters after the first (IKSI) over sequence repetition. We calculated the average IKSI for letter positions two through six and then averaged over position to get the mean IKSI. RT and IKSI averages were calculated only for sequences typed without error, and we excluded keystrokes with latencies greater than 3000 ms. Analyses were conducted on within-subject averages that were calculated for each combination of sequence condition (spin or Latin square) and presentation number (1 to 40). Because the first and second halves of the experiment were identical in structure, we collapsed over the halves (i.e., corresponding blocks in each half of the experiment were averaged).

We conducted Mauchly's (1940) test to check for violations of the sphericity assumption for analyses involving presentation number. Correcting for violations of the sphericity assumption using the Huynh and Feldt (1976) method did not change any of the conclusions we draw from these analyses. Thus, for the sake of brevity and clarity, we omit Mauchly's test results and report uncorrected analyses alongside the Huynh-Feldt estimated epsilon value. All t tests are supplemented with Jeffrey–Zellner–Siow Bayes factors (BF; Rouder, Speckman, Sun, Morey, & Iverson, 2009). These BF are likelihood ratios that reflect how many times more likely the data are under one hypothesis than under the other hypothesis. A BF of 2 in favor of the null hypothesis indicates that the data are two times as likely assuming the null hypothesis than they are assuming the alternative hypothesis, for example.

Ultimately, we want to know whether learning is faster for spin list sequences than Latin square sequences. Normally, an ANOVA interaction analysis would be appropriate to test for this difference. However, participants received extensive training on each sequence, and we did not know a priori how quickly the difference would emerge. If the difference emerges quickly and performance reaches asymptote quickly, then there would be few blocks in which performance diverges. If, on the other hand, the difference emerges slowly over the course of practice, then there would be several blocks in which performance diverges. The interaction would likely indicate a learning difference in the second case but not in the first. We report the ANOVA interactions in our tables, but because they are sensitive to learning rates, we do not discuss these analyses.

To test for learning differences, we conducted interaction contrast analyses for error rate, RT, and IKSI. For first block means, we assigned contrast weights of 39 and -39 to spin list and Latin square means, respectively. For means in each of the subsequent blocks, we assigned contrast weights of -1 and 1 to spin list and Latin square means, respectively. These contrasts compute how much performance changed for each sequence type (by comparing first block performance with the average of performance in blocks two through 40) and then compare the performance changes. Like the ANOVA interaction, a significant result indicates a difference in learning. Unlike the ANOVA interaction, it is not sensitive to when the learning difference emerges because performance after the first block is averaged. We supplement these interaction contrasts with *t* tests on first block performance to assess whether learning differences were driven by preexperimental differences in performance.

Means are displayed in Figure 1. Participants encoded and typed both spin list and Latin square sequences more quickly with practice, supported by simple main effects of presentation number on RT and IKSI for each sequence type (see Table 2). Error rate did not reduce significantly for either sequence type over the course of practice (see Table 2). The lack of improvement in accuracy was likely due to the accuracy of individual keystrokes being near ceiling. 80.6% of all sequences were typed without error. Typing a sequence without error requires 6 correct keystrokes, so the accuracy for individual keystrokes is roughly the 6th root of sequence accuracy. Roughly 96% of all keystrokes were correct. Little improvement occurred, but there was little room for improvement. The novel nature of the sequences and the instruction to type as quickly as possible may account for the lower ceiling accuracy compared with natural typing (80.6% in the experiment vs. 93.8% in paragraph typing).

Critically, spin list sequences were typed more quickly and (despite nonsignificant improvements in accuracy overall) typed more accurately than Latin square sequences over practice, supported by significant interaction contrast analyses for IKSI and error rate (see Table 3). There were no preexperimental differences in error rate, RT, or IKSI between spin list and Latin square sequences, supported by nonsignificant *t* tests on first block performance and BFs that favor the null hypothesis (see Table 3). The IKSI and error rate learning advantages for spin list sequences are consistent with participants learning item-to-item associations over practice. It is interesting to note that we found no learning advantage in RT, which reflects the time to encode the sequence, to prepare responses, and to execute the first keystroke. RTs were faster overall for spin list sequences, however (see Table 2). The associations that are formed over practice make transitioning between letters easier, but they seem to confer little-to-no advantage to sequence encoding and response preparation.

Participants could have formed associations between letters and their sequence position. They could have also formed associations between letters and their display positions because each had to occupy different positions on the computer screen (Oberauer, 2003; Schuck, Gaschler, Keisler, & Frensch, 2012). These position-to-item associations should strengthen over the course of the experiment because each sequence—and thus each position and item pair—repeated multiple times. However, because absolute position is inconsistent between anagram sequences for both sequence types, position-to-item associations should interfere and consequently play little or no role in the learning of each sequence. The sequence types also did not differ on the number of times a letter was presented in a particular position, so the spin list learning advantage cannot be attributed to differences in the strength of position-to-item associations between sequence types.

Skilled typing depends on the guidance of word-level representations (Crump & Logan, 2010b; Shaffer & Hardwick, 1968; Yamaguchi & Logan, 2014b). It is possible that word-like sequence representations were formed over the course of practice because each sequence was presented several times. The learning we see in Latin square sequences, which cannot be the result of item-to-item or position-to-item associations, could be attributed to the formation of sequence representations. Sequence representations cannot account for the spin list learning advantage, however. Each sequence was repeated equally often, so there was equal opportunity to create whole-sequence representations of each sequence type.

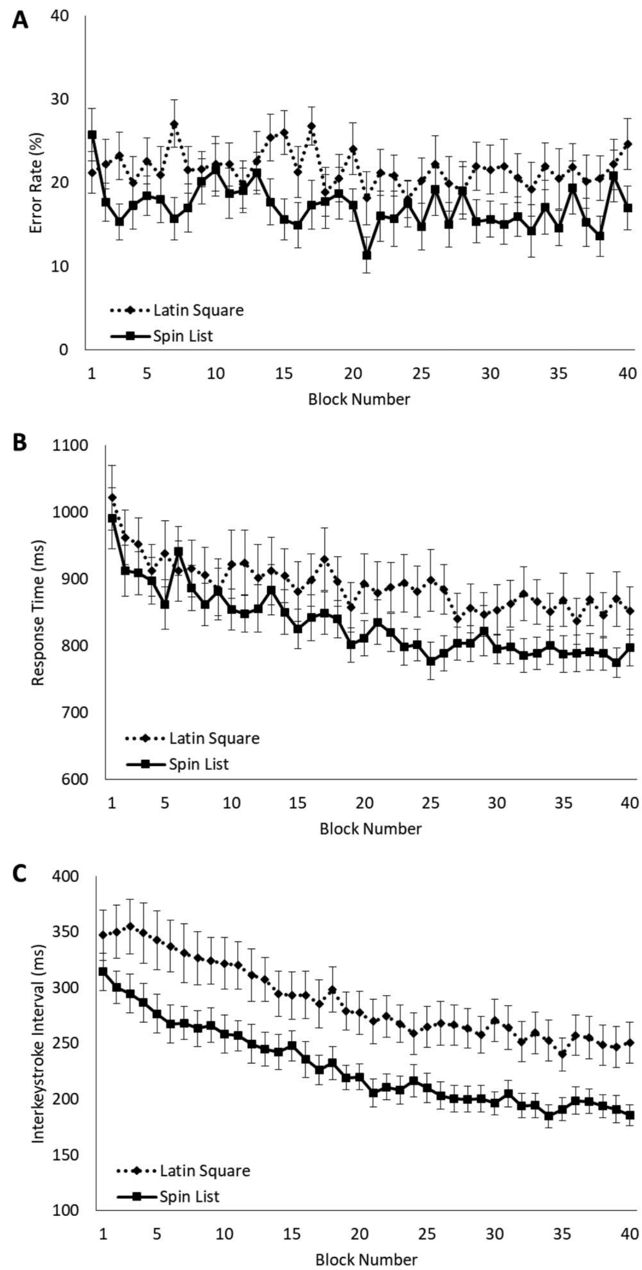

Figure 1. Experiment 1: Mean error rate (Panel A), response time (Panel B), and interkeystroke interval (Panel C) for each sequence type as a function of the presentation number of the sequence (block number). The bars are standard errors of the means.

Table 2
Experiment 1: ANOVA and Simple Main Effect Analyses for Training Effects

DV and type	*F*	*df*s	*MSE*	*p*	ϵ	η_p^2
Error rate						
Spin vs. Latin square	11.003	1, 23	.088	.003	1.000	.324
Type × Presentation	1.005	39, 897	.012	.464	.805	.420
Presentation (spin)	1.375	39, 897	.012	.065	.716	.056
Presentation (Latin square)	0.925	39, 897	.012	.603	.874	.039
RT						
Spin vs. Latin square	5.315	1, 23	297,757	.031	1.000	.188
Type × Presentation	1.591	39, 897	5,906	.013	.642	.065
Presentation (spin)	9.924	39, 897	5,906	<.001	.517	.301
Presentation (Latin square)	5.635	39, 897	5,906	<.001	.527	.197
IKSI						
Spin vs. Latin square	10.528	1, 23	160,603	.004	1.000	.314
Type × Presentation	0.838	39, 897	848	.750	.346	.035
Presentation (spin)	36.176	39, 897	848	<.001	.340	.611
Presentation (Latin square)	34.113	39, 897	848	<.001	.238	.597

Note. DV = dependent variable; RT = response time; IKSI = interkeystroke interval; ANOVA = analysis of variance.

The spin list advantage is consistent with the finding that typing is sensitive to similarities between letter strings (Crump & Logan, 2010a; Snyder & Logan, 2014). Spin list sequences are more similar to one another than Latin square sequences are to one another. Each spin list sequence overlaps with the other spin list sequences. For example, *tpgubk* (Table 1: Item 1, First Half) and *ktpgub* (Table 1: Item 6, First Half) share a run of 5 letters. Latin square sequences, on the other hand, do not have overlapping runs of letters. A spin list advantage might be obtained because spin list sequences produce more highly correlated sequence-level representations.

Experiment 2

The spin list learning advantage found in Experiment 1 is consistent with the formation of item-to-item associations, but it is also consistent with sequence similarity. It is not possible to distinguish among these alternatives by examining the rate of learning alone. It is, however, possible to distinguish among these alternatives by examining how practice on spin list sequences transfers to unpracticed sequences. We lay out the predictions of each alternative in Experiment 3. First, it must be demonstrated that practice on spin list sequences transfers at all. This was the aim of Experiment 2.

Participants practiced typing only four of the six spin list and Latin square sequences in the training portion of the experiment. After extensive practice with these sequences, they practiced typing the remaining two spin list and Latin square sequences in the test portion. We expect typing to be quicker and more accurate for spin list sequences than Latin square sequences in the training portion. If participants are forming item-to-item associations, then practice on spin list sequences should also produce positive transfer to untrained spin list sequences. Typing performance on spin list sequences in the test portion should be superior to initial performance on spin list sequences in the training portion.

Method

Participants. We tested 24 participants, each of whom was a native English speaker between the ages of 18 and 35 and reported normal or corrected-to-normal vision. Participants had 11.04 years of typing experience on average, and all but 2 participants had

Table 3
Experiment 1: The t Tests for First Block Performance and Interaction Contrasts

DV and test (A vs. B)	*t*	*df*	$M_{\text{A-B}}$	$SE_{\text{A-B}}$	*p*	*d*	BF
Error rate							
SB1 vs. LB1	1.380	23	.045	.033	.181	.282	2.013 (N)
Contrast	2.881	23	3.598	1.249	.004	.588	5.587 (A)
RT							
SB1 vs. LB1	−1.148	23	−31.309	27.263	.263	−.234	2.588 (N)
Contrast	1.192	23	1,044.348	876.178	.123	.243	2.476 (N)
IKSI							
SB1 vs. LB1	−1.420	23	−32.892	23.155	.169	−.290	1.919 (N)
Contrast	3.187	23	1,058.383	332.090	.002	.243	10.309 (A)

Note. For Bayes factors (BF), numbers followed by (A) indicate evidence in favor of the alternative hypothesis, and numbers followed by (N) indicate evidence in favor of the null hypothesis. SB1 = Spin list, Block 1 of training; LB1 = Latin square, Block 1 of training; DV = dependent variable; RT = response time; IKSI = interkeystroke interval.

formal typing training. In the preexperimental typing test, participants typed 93.26% of the words without error, and they typed 69.17 words per minute. The participants were tested in 1 hr timeslots and received $12 or course credit as compensation.

Apparatus and stimuli. We first generated 4 sets of 6 stimuli −2 spin list sets and 2 control sets—in the same way described in the first experiment. We then rearranged these sets to form training and test sets. The spin list training set contained 8 spin list sequences −4 stimuli from each of the initial spin list sets. The spin list test set contained the remaining two stimuli from each of the initial spin list sets (a total of 4 stimuli). The training and test sets of Latin square sequences were created using the same process. Table 4 shows the construction of stimuli in Experiment 2.

Procedure. In the training section of the experiment, the set of 16 training stimuli (8 spin list and 8 control) repeated 40 times each for a total of 640 training trials. The stimuli were blocked by number of repetitions and selected randomly within each block. Self-paced breaks were provided every 160 trials, except after Trial 640. After the final training trial, participants immediately transitioned to the test trials with no warning or break in between. The test trials were structured identically to the training trials. Each of the 8 test stimuli were repeated 6 times for a total of 48 test trials. Participants completed a total of 688 trials.

Results and Discussion

We calculated within-subject averages for each combination of sequence condition and block number. In both the training and test portion, we collapsed over the two sets of spin list sequences and over the two sets of Latin square sequences. One participant was omitted from training portion RT and IKSI analyses for making an incorrect keystroke in all Latin square sequences in one block. Three participants were omitted from RT and IKSI analyses on test portion blocks for making an incorrect keystroke on all Latin square sequences in a test block.

Mean performance across the experiment is shown in Figure 2.

Table 4
Construction of Letter Sequences in Experiment 2

Spin list set							Latin square set						
Training							Training						
Item 1	*t*	*p*	*g*	*u*	*b*	*k*	Item 9	*q*	*f*	*w*	*m*	*s*	*l*
Item 2	*p*	*g*	*u*	*b*	*k*	*t*	Item 10	*f*	*m*	*q*	*l*	*w*	*s*
Item 3	*g*	*u*	*b*	*k*	*t*	*p*	Item 11	*m*	*l*	*f*	*s*	*q*	*w*
Item 4	*u*	*b*	*k*	*t*	*p*	*g*	Item 12	*l*	*s*	*m*	*w*	*f*	*q*
Item 5	*y*	*z*	*c*	*n*	*r*	*d*	Item 13	*x*	*h*	*o*	*i*	*j*	*v*
Item 6	*z*	*c*	*n*	*r*	*d*	*y*	Item 14	*h*	*i*	*x*	*v*	*o*	*j*
Item 7	*c*	*n*	*r*	*d*	*y*	*z*	Item 15	*i*	*v*	*h*	*j*	*x*	*o*
Item 8	*n*	*r*	*d*	*y*	*z*	*c*	Item 16	*v*	*j*	*i*	*o*	*h*	*x*
Test							Test						
Item 1	*b*	*k*	*t*	*p*	*g*	*u*	Item 5	*s*	*w*	*l*	*q*	*m*	*f*
Item 2	*k*	*t*	*p*	*g*	*u*	*b*	Item 6	*w*	*q*	*s*	*f*	*l*	*m*
Item 3	*r*	*d*	*y*	*z*	*c*	*n*	Item 7	*j*	*o*	*v*	*x*	*i*	*h*
Item 4	*d*	*y*	*z*	*c*	*n*	*r*	Item 8	*o*	*x*	*j*	*h*	*v*	*i*

Note. These letters serve as examples. Each participant received a different random selection of letters. When presented on the computer screen, the spaces between letters were removed.

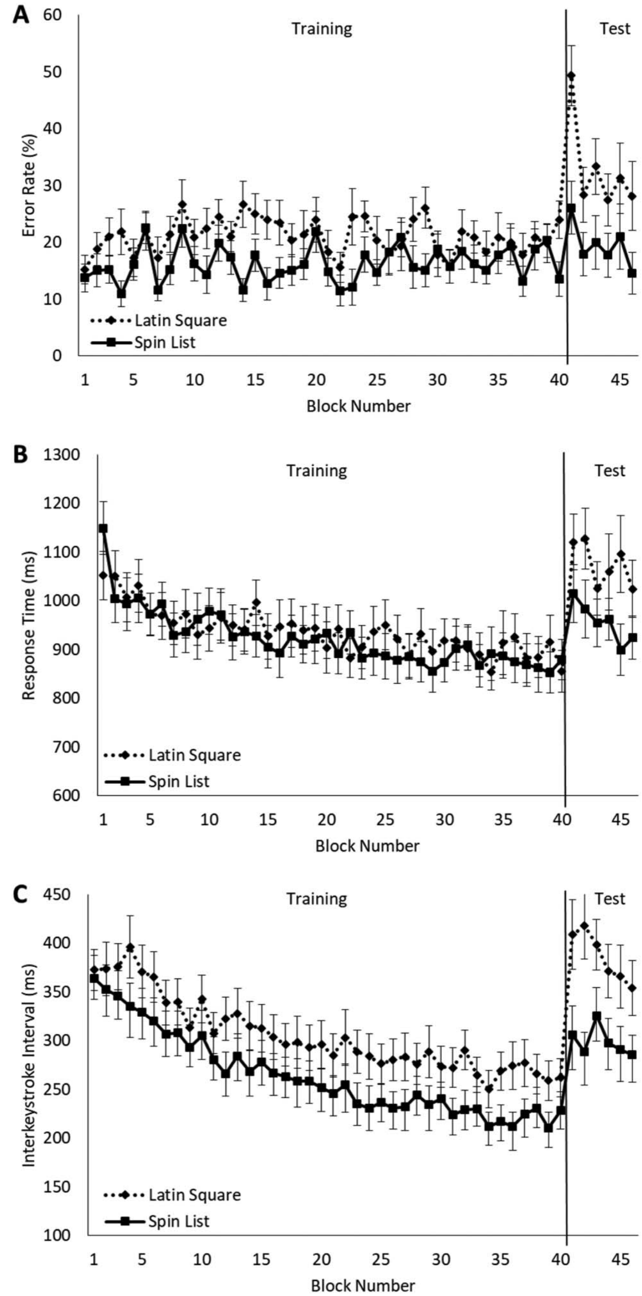

Figure 2. Experiment 2: Mean error rate (Panel A), response time (Panel B), and interkeystroke interval (Panel C) for each sequence type as a function of experiment block. Participants practiced training sequences in blocks 1 through 40 and test sequences in blocks 41 through 46. The bars are standard errors of the means.

In the training portion, RT and IKSI improved over practice for both sequence types (see Table 5). However, error rate did not significantly reduce for either sequence type (see Table 5), suggesting that keystroke accuracy was again near ceiling (roughly 97% of all keystrokes were correct). Replicating the critical result of Experiment 1, the interaction contrast was significant for IKSI; over practice in the training portion, spin list sequences were typed

Table 5
Experiment 2: ANOVA and Simple Main Effect Analyses for Training and Transfer Effects

DV and type	*F*	*df*s	*MSE*	p	ϵ	η_p^2
Error rate						
Spin vs. Latin square	8.889	1, 23	.129	.007	1.000	.279
Type × Presentation	1.147	39, 897	.016	.250	.857	.048
Presentation (spin)	1.370	39, 897	.016	.067	.764	.056
Presentation (Latin square)	1.348	39, 897	.016	.078	.709	.055
Type × Start Portion	5.171	1, 23	.065	.033	1.000	.184
Start portion (spin)	1.692	1, 23	.065	.206	1.000	.069
Start portion (Latin square)	20.402	1, 23	.065	<.001	1.000	.470
End portion (spin)	0.910	1, 23	.046	.350	1.000	.105
End portion (Latin square)	24.023	1, 23	.046	<.001	1.000	.755
RT						
Spin vs. Latin square	0.792	1, 22	310,414	.383	1.000	.035
Type × Presentation	1.577	39, 858	9,142	.015	.497	.067
Presentation (spin)	7.711	39, 858	9,142	<.001	.712	.260
Presentation (Latin square)	4.944	39, 858	9,142	<.001	.460	.183
Type × Start Portion	6.269	1, 20	70,990	.021	1.000	.239
Start portion (spin)	3.512	1, 20	70,990	.076	1.000	.149
Start portion (Latin square)	2.314	1, 20	70,990	.144	1.000	.104
End portion (spin)	8.166	1, 20	52,633	.010	1.000	.558
End portion (Latin square)	41.309	1, 20	52,633	<.001	1.000	.865
IKSI						
Spin vs. Latin square	6.452	1, 22	132,850	.019	1.000	.227
Type × Presentation	1.041	39, 858	1,495	.403	.425	.045
Presentation (spin)	26.526	39, 858	1,495	<.001	.370	.547
Presentation (Latin square)	20.773	39, 858	1,495	<.001	.385	.486
Type × Start Portion	9.358	1, 20	6,631	.006	1.000	.319
Start portion (spin)	14.410	1, 20	6,631	.001	1.000	.419
Start portion (Latin square)	0.884	1, 20	6,631	.358	1.000	.042
End portion (spin)	118.326	1, 20	3,617	<.001	1.000	.855
End portion (Latin square)	252.151	1, 20	3,617	<.001	1.000	.927

Note. ”Presentation” analyses only include the 40 training blocks. “Start portion” and “End portion” analyses compare the 6 test blocks to the first 6 blocks and last 6 blocks of training, respectively. DV = dependent variable; RT = response time; IKSI = interkeystroke interval; ANOVA = analysis of variance.

more quickly than Latin square sequences (see Table 6). IKSI did not differ between sequence types in the first block (see Table 6), suggesting that the learning difference was not the result of pre-experimental differences in typing speed.

Unlike Experiment 1, spin list sequences were not typed more accurately than Latin square sequences over practice; the contrast was not significant for error rate (see Table 6). It is possible that accuracy advantage we saw in Experiment 1 was spurious. However, we think it is more likely that the effect is volatile; keystroke accuracy is near ceiling, and sequence accuracy is highly variable over practice (small, random fluctuations in keystroke accuracy are exacerbated at the level of sequence accuracy).

Also unlike Experiment 1, the interaction contrast is significant for RT (see Table 6). However, RT was higher on average for spin list sequences than Latin square sequences in the first block (see Table 6). Additionally, RT was overall no different between the

Table 6
Experiment 2: The t Tests for First Block Performance and Interaction contrasts

DV and test (A vs. B)	*t*	*df*	$M_{A\text{-}B}$	$SE_{A\text{-}B}$	*p*	*d*	BF
Error rate							
SB1 vs. LB1	−0.482	23	−0.015	0.031	.634	−.098	4.190 (N)
Contrast	0.949	23	1.368	1.442	.176	.194	3.108 (N)
RT							
SB1 vs. LB1	3.038	23	97.516	32.101	.006	.620	7.622 (A)
Contrast	4.163	23	4,537.960	1,090.151	<.001	.850	83.241 (A)
IKSI							
SB1 vs. LB1	−0.519	23	−9.004	17.342	.609	−.106	4.120 (N)
Contrast	2.920	23	1,287.253	440.786	.004	.596	6.032 (A)

Note. For Bayes factors (BF), numbers followed by (A) indicate evidence in favor of the alternative hypothesis, and numbers followed by (N) indicate evidence in favor of the null hypothesis. SB1 = Spin list, Block 1 of training; LB1 = Latin square, Block 1 of training; DV = dependent variable; RT = response time; IKSI = interkeystroke interval.

two sequence types, indicated by a nonsignificant main effect of sequence type (see Table 5). It is unclear whether the significant contrast reflects a genuine learning advantage or simply preexperimental differences between items.

Performance on the six test portion blocks is shown in comparison to performance on the first six and last six training blocks in Figure 3 and Figure 4 for spin list sequences and Latin square sequences, respectively. Untrained spin list sequences were typed more quickly than spin list sequences at the start of training,

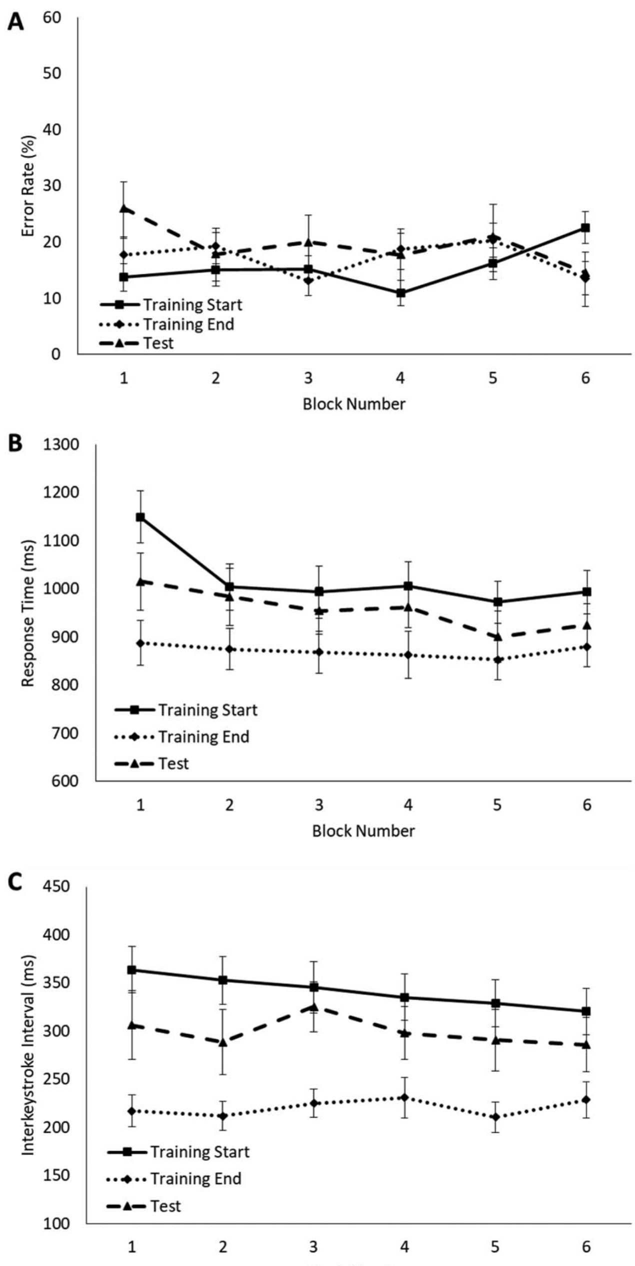

Figure 3. Experiment 2: Mean error rate (Panel A), response time (Panel B), and interkeystroke interval (Panel C) for spin list sequences in the test portion compared with spin list sequences at the start and end of the training portion. The bars are standard errors of the means.

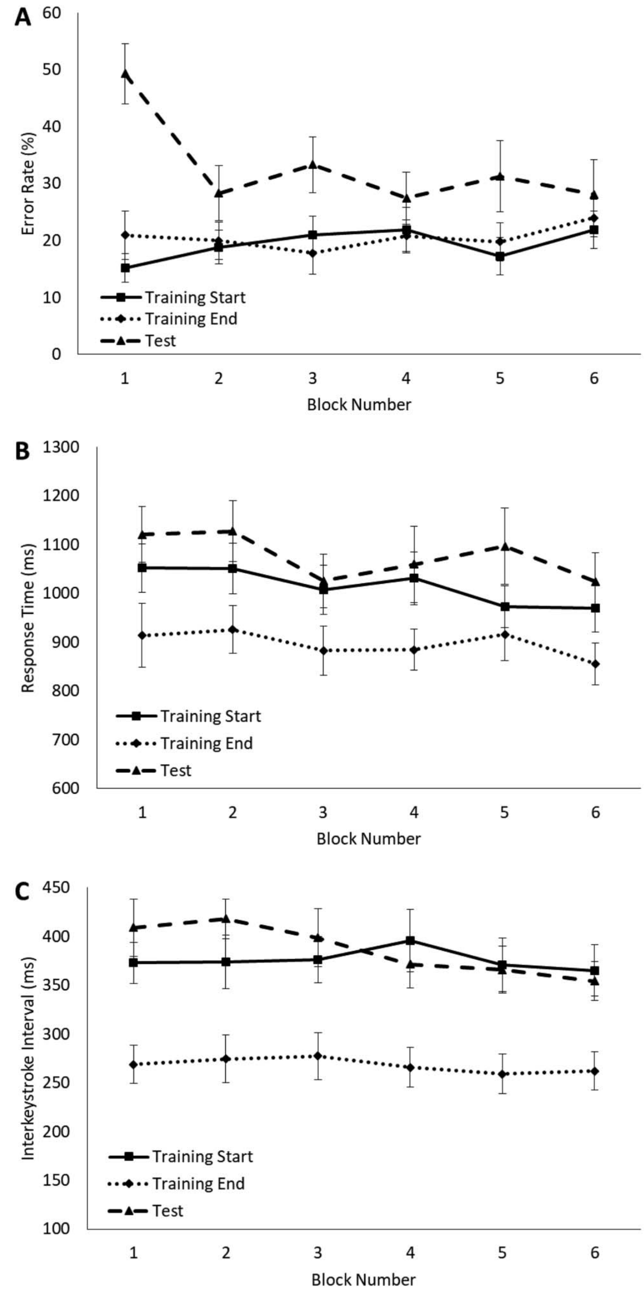

Figure 4. Experiment 2: Mean error rate (Panel A), response time (Panel B), and interkeystroke interval (Panel C) for Latin square sequences in the test portion compared with Latin square sequences at the start and end of the training portion. The bars are standard errors of the means.

supported by a significant simple main effect analysis comparing performance in the six test portion blocks with performance in the first six training blocks (see Table 5). The change in performance from start of training to test was greater for spin list sequences than Latin square sequences, supported by a significant sequence type by experiment portion interaction (see Table 5). Training on spin list sequences produced positive transfer to untrained spin list sequences, consistent with the formation of item-to-item associations over practice. The benefit for spin list sequences in the test portion cannot be explained by participants simply getting better at the task because transfer was larger for spin list sequences. Untrained spin list sequences were typed more slowly than spin list sequences at the end of training, however, supported by a significant simple main effect analysis comparing test performance with performance in the last six training blocks (see Table 5). Transfer was imperfect, suggesting that item-to-item associations are not the only contributor to learning. Whole-sequence representations or position-to-item associations, which would not transfer to new spin list sequences, could have also supported the improvements in typing speed in the training portion.

We found no transfer benefits for spin list sequence error rate (see Table 5), which is unsurprising because keystroke accuracy was near ceiling. Although RT for untrained spin list sequences were numerically better in the test portion than at the beginning of training, the difference was not significant (see Table 5). The item-to-item associations formed during training seem to confer little advantage to the encoding of untrained spin list sequences.

RT and IKSI for untrained Latin square sequences were no different than for Latin square sequences at the start of training (see Table 5). Error rates, on the other hand, were higher for new Latin square sequences (see Table 5). Training on Latin square sequences seemed to have produced some interference in the learning of new Latin square sequences. It is not clear why this interference did not extend to RT or IKSI. Regardless, we found no evidence of positive transfer for Latin square sequences, suggesting that the positive transfer found for spin list sequences is not explainable by participants simply getting better at the task.

Experiment 3

In Experiment 2, we demonstrated that training on spin list sequences transfers to new spin list sequences, but the same is not true for Latin square sequences. Like the spin list learning advantage, the transfer found for spin list sequences could be attributed to the consistent relative order of items, which foster the development of item-to-item associations, or to overlapping runs of items, which could produce more similar sequence representations. In Experiment 3, we aimed to dissociate these alternatives by observing transfer patterns. Participants train on just one sequence from a set, and they transfer to all sequences in the set. With this design, we can observe how transfer of training depends on the spin distance of the tested sequence from the trained sequence.

We characterize spin distance in terms of magnitude and direction. We treat the list as a circle (picture a clock face e.g.), with the letters at the start and end of the sequence occupying adjacent locations on the circular list. We define spin magnitude as the number of positions that each letter in the tested sequence has moved on the circle, relative to the trained sequence. We define spin direction as positive (clockwise in the imagined circular list) or negative (counterclockwise in the circular list). Moving an item from one end position to the other requires a shift of just one position, even though the item has shifted five positions to the right or left in the presented list.

Example transfer patterns are laid out graphically in Figure 5. First consider if item-to-item associations are the source of the transfer effect (Panel A in Figure 5). When learning a 6-letter sequence, participants would learn 5 item-to-item associations: one

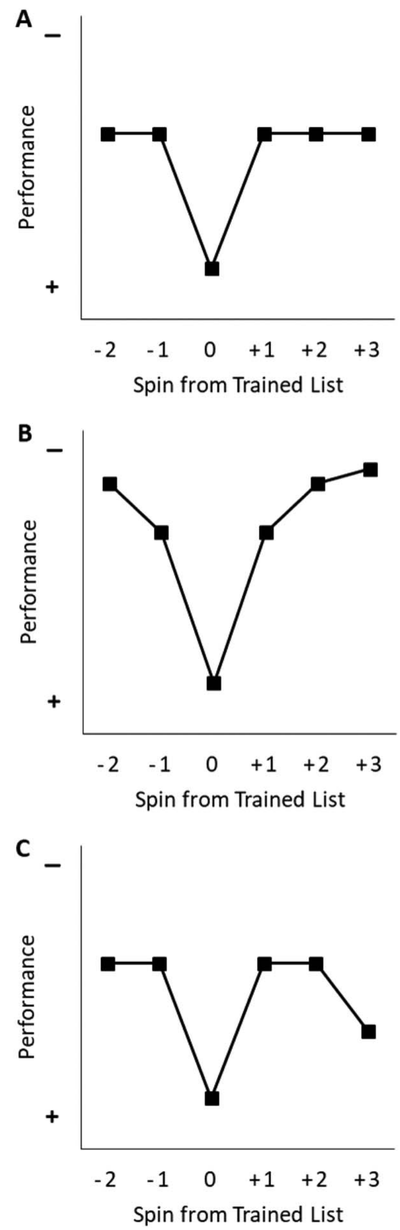

Figure 5. Experiment 3: Transfer predictions for item-to-item associations (A), sequence similarity (B), and trigram chunking (C). Performance (+ for better performance, − for worse performance) is shown as a function of the test sequences' spin distance from the trained sequence. Note that better performance is lower on the vertical axis, because lower error rate, RT, and IKSI is indicative of better performance.

between the letters in positions one and two, one between the letters in positions two and three, and so on. The magnitude of transfer should depend on how many of the learned associations are present in the test sequence. We should see maximum transfer to the same sequence (spin 0) because all five item-to-item associations are shared between the trained and tested sequences. Transfer to all other test sequences should be equivalent, because each of the other spins of the sequence share four of the five item-to-item associations (only the association between edge letters is lost).

Now consider if sequence similarity is the source of the transfer effect (Panel B in Figure 5). Similarity and spin magnitude should be negatively related because sequences with higher magnitude spins have fewer overlapping runs of letters with the trained sequence. Maximum transfer should again be obtained for the same sequence because a sequence is more similar to itself than to various spins of the sequence. There should be a monotonic transfer gradient for the remaining spins of the sequence, with higher transfer to sequences with lower magnitude spins (e.g., spin +1, spin −1) than to sequences with higher magnitude spins (e.g., spin −2, spin +2). Item-to-item associations and sequence similarity predict qualitatively different transfer patterns for spun sequences: Item-to-item associations predict no differences in transfer among spun sequences, and sequence similarity predicts a negative relationship between transfer and spin magnitude.

Table 7
Construction of Letter Sequences in Experiment 3

Spin list sets													
Training							Test						
Set 1	*t*	*p*	*g*	*u*	*b*	*k*	Set 1, Spin 0	*t*	*p*	*g*	*u*	*b*	*k*
Set 2	*y*	*z*	*c*	*n*	*r*	*d*	Set 1, Spin −1	*p*	*g*	*u*	*b*	*k*	*t*
Set 3	*q*	*f*	*m*	*l*	*s*	*w*	Set 1, Spin −2	*g*	*u*	*b*	*k*	*t*	*p*
Set 4	*x*	*h*	*i*	*v*	*j*	*o*	Set 1, Spin +3	*u*	*b*	*k*	*t*	*p*	*g*
							Set 1, Spin +2	*b*	*k*	*t*	*p*	*g*	*u*
							Set 1, Spin +1	*k*	*t*	*p*	*g*	*u*	*b*
							Set 2, Spin 0	*y*	*z*	*c*	*n*	*r*	*d*
							Set 2, Spin −1	*z*	*c*	*n*	*r*	*d*	*y*
							Set 2, Spin −2	*c*	*n*	*r*	*d*	*y*	*z*
							Set 2, Spin +3	*n*	*r*	*d*	*y*	*z*	*c*
							Set 2, Spin +2	*r*	*d*	*y*	*z*	*c*	*n*
							Set 2, Spin +1	*d*	*y*	*z*	*c*	*n*	*r*
							Set 3, Spin 0	*q*	*f*	*m*	*l*	*s*	*w*
							Set 3, Spin −1	*f*	*m*	*l*	*s*	*w*	*q*
							Set 3, Spin −2	*m*	*l*	*s*	*w*	*q*	*f*
							Set 3, Spin +3	*l*	*s*	*w*	*q*	*f*	*m*
							Set 3, Spin +2	*s*	*w*	*q*	*f*	*m*	*l*
							Set 3, Spin +1	*w*	*q*	*f*	*m*	*l*	*s*
							Set 4, Spin 0	*x*	*h*	*i*	*v*	*j*	*o*
							Set 4, Spin −1	*h*	*i*	*v*	*j*	*o*	*x*
							Set 4, Spin −2	*i*	*v*	*j*	*o*	*x*	*h*
							Set 4, Spin +3	*v*	*j*	*o*	*x*	*h*	*i*
							Set 4, Spin +2	*j*	*o*	*x*	*h*	*i*	*v*
							Set 4, Spin +1	*o*	*x*	*h*	*i*	*v*	*j*

Note. These letters serve as examples. Each participant received a different random selection of letters. When presented on the computer screen, the spaces between letters were removed. All sequences came from spin list sets. Test sequences are named according to the set from which they originated (indicating the set of letters used) and the spin distance from the trained sequence. The magnitude of distance indicates how far each letter in the test sequence is displaced from its original position in the trained sequence. The valence of the distance indicates the direction of displacement (positive = right spin, negative = left spin).

Method

Participants. We tested 24 participants. Each participant was a native English speaker between the ages of 18 and 35 and reported normal or corrected-to-normal vision. Participants had 12.81 years of typing experience on average, and all had formal typing training. In the preexperimental typing test, participants typed 93.49% of the words without error, and they typed 80.09 words per minute. The participants were tested in 1 hr timeslots and received $12 or course credit as compensation.

Apparatus and stimuli. We again generated 4 sets of 6 stimuli. Unlike the previous experiments, all 4 sets were spin list sets (constructed in the same manner as before); there were no Latin square sequences. The training stimulus set contained 4 stimuli—one from each of the 4 sets. The transfer stimulus set was created by combining all 4 spin lists sets, yielding a set of 24 stimuli. Table 7 shows the construction of stimuli in Experiment 3.

Procedure. Participants first completed the training section of the experiment, during which they saw each of the 4 training stimuli 40 times for a total of 160 training trials. Participants then completed the test section, during which they saw each of the 24 test stimuli 10 times for a total of 240 test trials. The participants were not explicitly informed that the switch would occur, and the test trials were structured identically to the training trials. In both sections, the stimuli were blocked by number of repetitions and selected randomly within each block. Participants completed a total of 400 trials and could take self-paced breaks every 80 trials.

Results and Discussion

Analyses were conducted on within-subject mean error rate, RT, and IKSI. For both the training and the test portion, we collapsed over the four sequence sets. Means were calculated for each repetition of the training sequences in the training portion. To assess transfer in the test portion, we calculated the means for each repetition of the untrained test portion sequences. To assess the pattern of transfer, we averaged over repetitions of the test portion sequences, and means were computed separately for each spin distance. Spin distance was defined by both the magnitude of displacement of the letters in the trained sequence (0 to 3) and the direction of the displacement (clockwise/positive or counterclockwise/negative). For example, if the training sequence was *tpgubk*, then test sequence *gubktp* would be scored as a −2 spin sequence (notice that the letter *g* in the first sequence has shifted left 2 positions). Because of the circular nature of spin list sequences, *gubktp* could also be scored as a + 5 spin sequence, but we choose to define sequences by their minimum spin magnitude. Because each sequence was 6 letters in length, a spin displacement of 3 could be either a + 3 spin or a − 3 spin. When displaying the transfer results, we chose to represent these as + 3 spin sequences. Four participants were omitted from ANOVA on the training portion RT and IKSI because they failed to type at least one sequence without error in all the training blocks. Two participants were omitted from RT and IKSI analyses on test block performance for making errors on all sequences in a test block.

Training and test portion means are shown as a function of experiment block in Figure 6. RT and IKSI improved over practice in the training portion, supported by significant simple main effects of presentation number (see Table 8). Error rate, however, did not change over practice (see Table 8). Keystroke accuracy was again near ceiling (roughly 96% of all keystrokes were correct).

Figure 7 displays means for untrained sequences in the 10 test blocks and the means for training sequences in first 10 and last 10

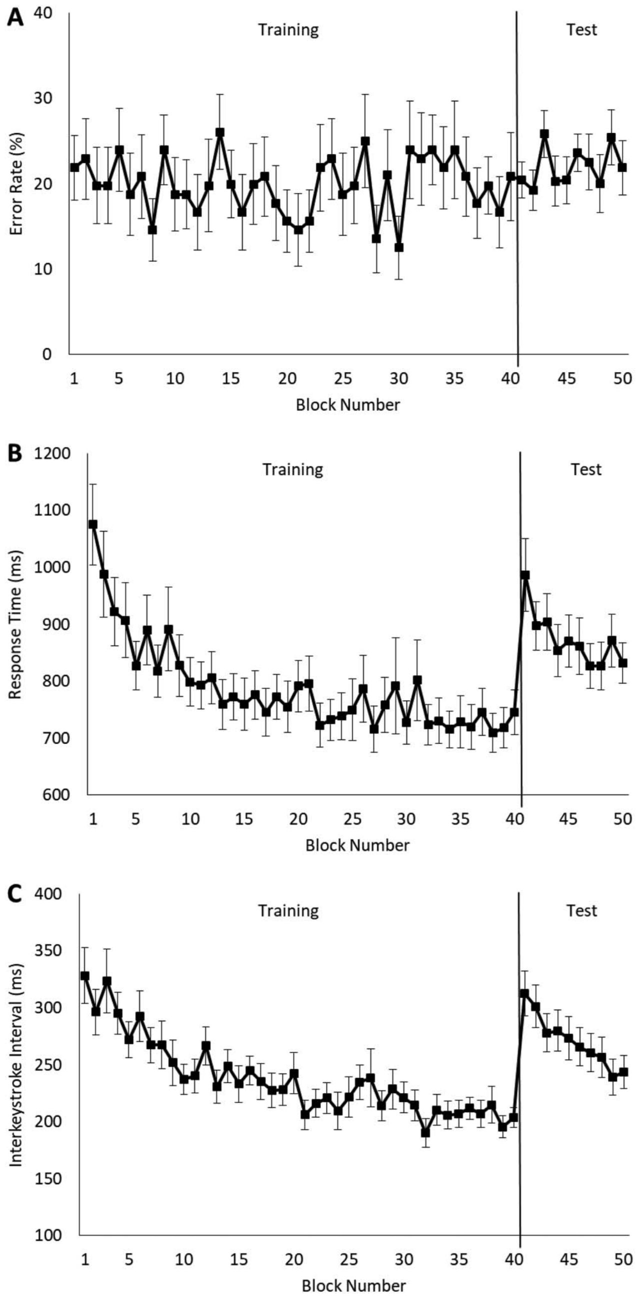

Figure 6. Experiment 3: Mean error rate (Panel A), response time (Panel B), and interkeystroke interval (Panel C) for spin list sequences as a function of experiment block. Participants practiced training sequences in blocks 1 through 40 and test sequences in blocks 41 through 50. Test portion means exclude spin 0 sequence trials. The bars are standard errors of the means.

blocks of training. Spun test sequences were typed more quickly than sequences at the start of training, supported by a significant simple main effect of experiment portion on IKSI (see Table 8). They were typed more slowly than sequences at the end of training, however (see Table 8). Like in Experiment 2, training on a sequence produced positive, imperfect transfer to spins of that sequence, consistent with participants using item-to-item associations to aid typing of the new sequences.

Replicating Experiment 2, untrained sequences were not typed more accurately or encoded more quickly than sequences at the beginning of training, indicated by nonsignificant simple main effects of experiment portion on error rate and RT (see Table 8). The lack of transfer in error rate is unsurprising given the lack of improvement over the course of training (keystrokes were already very accurate). The lack of transfer in RT suggests that the item-to-item associations formed during training do not confer much of an advantage to sequence encoding.

Average test portion means are shown as a function of spin distance in Figure 8. Transfer was found only for IKSI. Critically, the amount of transfer did not depend on spin distance, supported by a nonsignificant main effect of spin distance on IKSI for unspun test sequences (see Table 9). We obtained the BF for this analysis with the assistance of JASP (2016). The BF was 5.169 in favor of the null hypothesis. The lack of difference among spun sequences is consistent with item-to-item associations being the source of transfer.

We also tested the transfer predictions of sequence similarity directly using a contrast analysis. We assigned contrast weights of 1, −2, −2, 1, and 2 to sequences of spin −2, spin −1, spin +1, spin +2, and spin +3, respectively. Similarity predicts better transfer (lower IKSI) to test sequences with lower spin magnitude, so sequences with lower spin magnitudes were given lower weights. This contrast analysis was not significant (see Table 9), and the BF for this analysis again favored the null hypothesis of no difference among the means (BF = 3.771).

Experiment 4

The previous experiments demonstrated that item-to-item associations are learned with practice if the relative order of items in a sequence is consistent and that these associations aid in the typing of both learned and novel sequences. However, the results do not indicate the direction of the associations. In the associative memory literature, researchers have questioned whether item-to-item associations are symmetric or direction-specific—that is, whether item-to-item associations are stored as a single representation (Asch & Ebenholtz, 1962) or as separate forward and backward associations (Wolford, 1971). In Experiment 4, we ask whether item-to-item associations in typing are symmetric or direction specific. We address this question using a transfer of training task similar to Experiment 2. In Experiment 4, however, participants transferred to untrained sequences in which the order of items was opposite to the trained sequences. If item-to-item associations in typing are symmetric, then typing should be faster or more accurate for reversed spin list sequences than for spin list sequences at the start of training. If the associations are direction-specific, then typing performance on reversed spin list sequences should be no different, or perhaps worse, than performance on spin list sequences at the start of training.

Method

Participants. We tested 24 participants. Each participant was a native English speaker between the ages of 18 and 35 and reported normal or corrected-to-normal vision. Participants had

Table 8
Experiment 3: ANOVA and Simple Main Effect Analyses for Training and Transfer Effects

DV and type	F	dfs	MSE	p	ϵ	η_p^2
Error rate						
Presentation (training)	0.871	39, 897	.030	.696	.751	.036
Start portion	0.402	1, 23	.062	.532	1.000	.017
End portion	0.135	1, 23	.045	.717	1.000	.006
Spin distance	0.818	4, 92	.007	.517	.998	.034
RT						
Presentation (training)	7.727	39, 741	14,890	<.001	.260	.289
Start portion	0.001	1, 21	116,949	.973	1.000	.000
End portion	34.951	1, 21	70,320	<.001	1.000	.625
Spin distance	0.861	4, 92	6,445	.490	.893	.036
IKSI						
Presentation (training)	11.356	39, 741	2,471	<.001	.284	.374
Start portion	4.418	1, 21	6,436	.048	1.000	.174
End portion	34.532	1, 21	14,471	<.001	1.000	.622
Spin distance	1.355	4, 92	625	.256	.945	.056

Note. "Presentation" analyses only include the 40 training blocks. "Start portion" and "end portion" analyses compare the 6 test blocks to the first 6 blocks and last 6 blocks of training, respectively. "Spin distance" analyses check for any difference among the means for spun sequences in the test portion (excluding spin 0 trials). ANOVA = analysis of variance; DV = dependent variable; RT = response time; IKSI = interkeystroke interval.

11.58 years of typing experience on average, and all had formal typing training. In the preexperimental typing test, participants typed 94.51% of the words without error, and they typed 86.37 words per minute. The participants were tested in 1.5 hr timeslots and received $18 or course credit as compensation.

Apparatus and stimuli. We generated 4 sets of 6 stimuli as we did in the first experiment. The stimuli from the 2 spin list sets were then combined into a training spin list set. The stimuli from the 2 control sets were likewise combined into a training control set. We then formed spin list and control test sets in which the stimuli were reversed copies of the spin list and control training stimuli (e.g., if a training set contained *dtnhwp*, then the test set contained *pwhntd*). Table 10 shows the construction of stimuli in Experiment 4. Due to the nature of the Latin square sequences, reversing the training sequences produced an identical set of test sequences (notice, e.g., that Item 13 in the Training Control set is equivalent to Item 16 in the Test Control set), so Latin square test trials were essentially additional training trials.

Procedure. In the training section of the experiment, participants saw each of the 24 training stimuli (12 spin list and 12 control) 40 times for a total of 960 training trials. The stimuli were blocked by number of repetitions and selected randomly within each block. Participants could take a self-paced break every 240 trials. Following the break after the final training trial, participants began the test trials. The participants were not explicitly informed that the switch would occur, and the test trials were structured identically to the training trials. Participants saw each of the 24 test stimuli 10 times for a total of 240 test trials. Participants completed a total of 1200 trials.

Results and Discussion

We calculated mean error rate, RT, and IKSI for each condition and each repetition block in the experiment. We collapsed over the two sets of spin list sequences and the two sets of Latin square sequences. Mean performance for all blocks is displayed in Figure 9. The results of Experiment 1 once again replicated. Participants encoded and typed both sequence types faster with practice, but because keystroke accuracy was near ceiling (97% correct), their sequence-level accuracy did not improve over practice (see Table 11). We again find a spin list learning advantage: Participants learned to type spin list sequences more quickly and (despite nonsignificant improvements overall) more accurately over practice (see Table 12). There were not initial differences in IKSI or error rate, suggesting that these differences emerged over training (see Table 12). Spin list sequences were not encoded more quickly than Latin square sequences over practice (see Table 12).

Performance on reversed spin list sequences is shown in comparison to training performance in Figure 10. RT for reversed spin list sequences were lower than for spin list sequences at the start of practice, supported by a significant simple main effect comparing RT in the 10 test blocks to RT in the first 10 training blocks (see Table 11). Participants were quicker to encode and begin typing the reversed sequences. However, the IKSI and error rate analyses indicate that they did not type the reversed sequences more quickly, and they typed the reversed sequences less accurately than sequences at the start of training (see Table 11). Initial training did not lead to improved typing of the reversed spin list sequences, so the item-to-item associations learned in typing are direction-specific, not symmetric.

General Discussion

We sought direct evidence for the use of item-to-item associations in typing. To obtain this evidence, we conducted four experiments inspired by Ebenholtz's (1963) spin list learning procedure. We argued that if typing makes use of item-to-item associations, then we should see (a) superior learning for spun sequences because relative order consistencies foster the development of item-to-item associations, (b) positive transfer to unlearned sequences with the same relative order because of shared item-to-

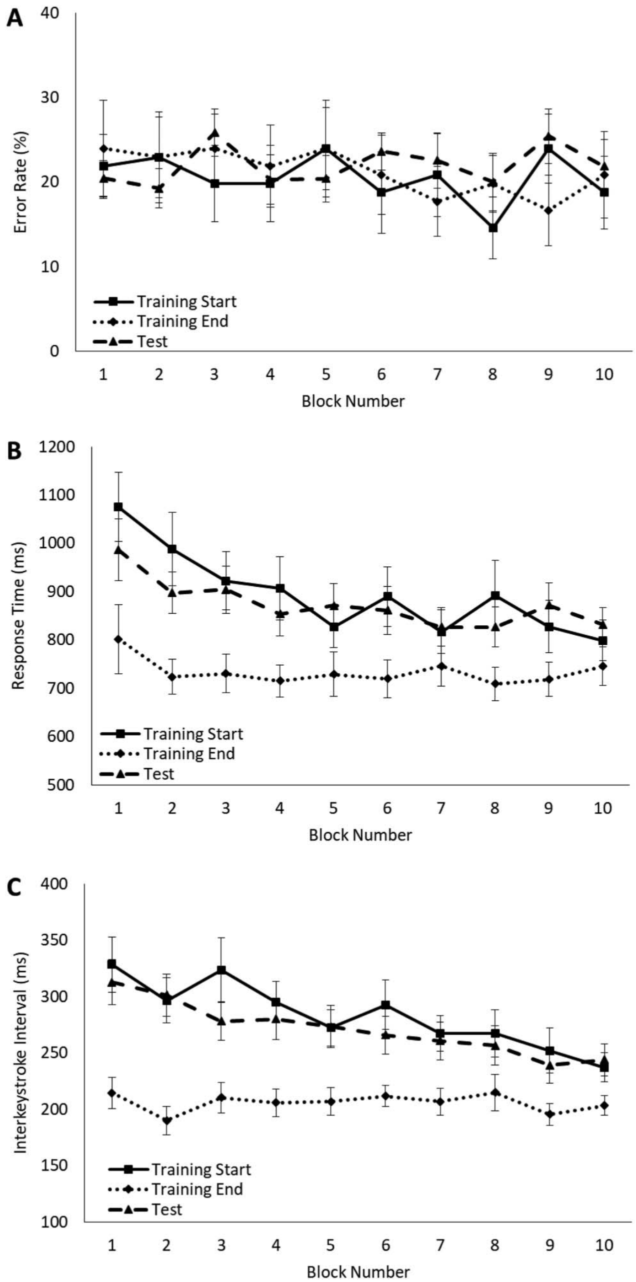

Figure 7. Experiment 3: Mean error rate (Panel A), response time (Panel B), and interkeystroke interval (Panel C) for spin list sequences in the test portion compared with spin list sequences at the start and end of the training portion. Test portion means exclude spin 0 sequence trials. The bars are standard errors of the means.

item associations, and (c) positive transfer that is insensitive to spin distance because only the number of shared associations—not their position in the sequence—matters. All three results were obtained, suggesting that item-to-item associations do influence how typists order their keystrokes. Finally, we addressed the directionality of these associations, demonstrating that forward associations are learned independently of backward associations.

What About Chunking?

In many skills, practice gives rise to hierarchical control. The development of hierarchical representations—or chunks—is one manner in which performance can be controlled hierarchically (Logan, in press). Chunking processes play a role in typing gen-

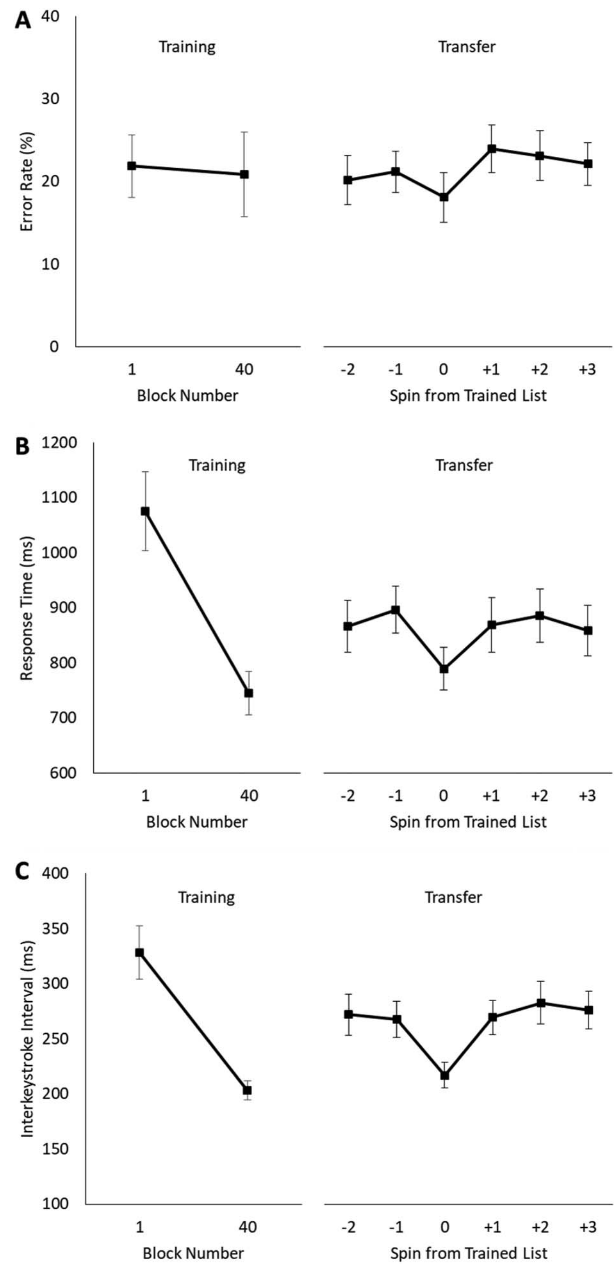

Figure 8. Experiment 3: Mean error rate (Panel A), response time (Panel B), and interkeystroke interval (Panel C) for spin list sequences in the test portion, shown as a function of their spin from the trained list. The magnitude of distance indicates how far each letter in the test sequence is displaced from their original positions in the trained sequence. The valence of the distance indicates the direction of displacement (positive = right spin, negative = left spin). Performance on the first and last blocks of training are shown for comparison. The bars are standard errors of the means.

Table 9
Experiment 3: The t Tests for Transfer Effects and Transfer Pattern Contrasts

DV and test (A vs. B)	*t*	*df*	$M_{\text{A-B}}$	$SE_{\text{A-B}}$	*p*	*d*	BF
Error rate							
NST vs. ST	−2.100	23	−0.040	.019	.047	−.430	1.368 (A)
Similarity (contrast)	−0.288	23	−0.029	.100	.612	−.059	4.486 (N)
Trigram (contrast)	−0.020	23	−0.002	.076	.508	−.004	4.658 (N)
RT							
NST vs. ST	−4.787	23	−85.453	17.853	<.001	−.977	333.765 (A)
Similarity (contrast)	0.212	23	20.233	95.554	.417	.043	4.564 (N)
Trigram (contrast)	1.111	23	81.385	73.287	.139	.227	2.686 (N)
IKSI							
NST vs. ST	−8.782	23	−56.193	6.392	<.001	−1.795	1,519,741 (A)
Similarity (contrast)	0.683	23	20.314	29.759	.251	.139	3.771 (N)
Trigram (contrast)	−0.520	23	−11.859	22.824	.696	−.106	4.120 (N)

Note. For Bayes factors (BF), numbers followed by (A) indicate evidence in favor of the alternative hypothesis, and numbers followed by (N) indicate evidence in favor of the null hypothesis. Similarity and trigram contrast analyses test the transfer predictions of similarity and trigram chunking, respectively. NST = test block no spin trials (only Spin 0); ST = test block spin trials (excluding Spin 0); DV = dependent variable; RT = response time; IKSI = interkeystroke interval.

erally: Typists tend to group letters into part-sequence chunks to help them type long words (Ostry, 1983). Chunking processes may have played a role in our experiments as well. Even though previously learned chunks were rendered useless by the nonword sequences, participants may have formed new chunks with practice because sequences—and thus groups of letters—repeated multiple times (Yamaguchi & Logan, 2016).

Table 10
Construction of Letter Sequences in Experiment 4

Spin list set							Control set						
Training							Training						
Item 1	*t*	*p*	*g*	*u*	*b*	*k*	Item 13	*q*	*f*	*w*	*m*	*s*	*l*
Item 2	*p*	*g*	*u*	*b*	*k*	*t*	Item 14	*f*	*m*	*q*	*l*	*w*	*s*
Item 3	*g*	*u*	*b*	*k*	*t*	*p*	Item 15	*m*	*l*	*f*	*s*	*q*	*w*
Item 4	*u*	*b*	*k*	*t*	*p*	*g*	Item 16	*l*	*s*	*m*	*w*	*f*	*q*
Item 5	*b*	*k*	*t*	*p*	*g*	*u*	Item 17	*s*	*w*	*l*	*q*	*m*	*f*
Item 6	*k*	*t*	*p*	*g*	*u*	*b*	Item 18	*w*	*q*	*s*	*f*	*l*	*m*
Item 7	*y*	*z*	*c*	*n*	*r*	*d*	Item 19	*x*	*h*	*o*	*i*	*j*	*v*
Item 8	*z*	*c*	*n*	*r*	*d*	*y*	Item 20	*h*	*i*	*x*	*v*	*o*	*j*
Item 9	*c*	*n*	*r*	*d*	*y*	*z*	Item 21	*i*	*v*	*h*	*j*	*x*	*o*
Item 10	*n*	*r*	*d*	*y*	*z*	*c*	Item 22	*v*	*j*	*i*	*o*	*h*	*x*
Item 11	*r*	*d*	*y*	*z*	*c*	*n*	Item 23	*j*	*o*	*v*	*x*	*i*	*h*
Item 12	*d*	*y*	*z*	*c*	*n*	*r*	Item 24	*o*	*x*	*j*	*h*	*v*	*i*
Test							Test						
Item 1	*k*	*b*	*u*	*g*	*p*	*t*	Item 13	*l*	*s*	*m*	*w*	*f*	*q*
Item 2	*t*	*k*	*b*	*u*	*g*	*p*	Item 14	*s*	*w*	*l*	*q*	*m*	*f*
Item 3	*p*	*t*	*k*	*b*	*u*	*g*	Item 15	*w*	*q*	*s*	*f*	*l*	*m*
Item 4	*g*	*p*	*t*	*k*	*b*	*u*	Item 16	*q*	*f*	*w*	*m*	*s*	*l*
Item 5	*u*	*g*	*p*	*t*	*k*	*b*	Item 17	*f*	*m*	*q*	*l*	*w*	*s*
Item 6	*b*	*u*	*g*	*p*	*t*	*k*	Item 18	*m*	*l*	*f*	*s*	*q*	*w*
Item 7	*d*	*r*	*n*	*c*	*z*	*y*	Item 19	*v*	*j*	*i*	*o*	*h*	*x*
Item 8	*y*	*d*	*r*	*n*	*c*	*z*	Item 20	*j*	*o*	*v*	*x*	*i*	*h*
Item 9	*z*	*y*	*d*	*r*	*n*	*c*	Item 21	*o*	*x*	*j*	*h*	*v*	*i*
Item 10	*c*	*z*	*y*	*d*	*r*	*n*	Item 22	*x*	*h*	*o*	*i*	*j*	*v*
Item 11	*n*	*c*	*z*	*y*	*d*	*r*	Item 23	*h*	*i*	*x*	*v*	*o*	*j*
Item 12	*r*	*n*	*c*	*z*	*y*	*d*	Item 24	*i*	*v*	*h*	*j*	*x*	*o*

Note. These letters serve as examples. Each participant received a different random selection of letters. When presented on the computer screen, the spaces between letters were removed.

The spin list learning advantage and the transfer findings in Experiment 2 are potentially explainable by chunking. In our spin list sequences, runs of letters often repeat, even among different sequences. Participants may have found it easier to group and form chunked representations of the letters as a result, expediting learning for these sequences. Practice would transfer to unpracticed sequences that shared the learned chunks. Transfer may be greater for spin list sequences if chunks are easier to form. Thus, it is important demonstrate that participants are not forming chunked representations of the letters.

To determine whether participants are chunking the letters, we define chunks operationally. Chunks have boundaries. Traversing the boundary of one chunk into another requires retrieval of the new chunk, then retrieval of the item within that chunk. The extra step of retrieving the new chunk generates a spike in latency (Farrell, 2012; Henson, 1996; Ostry, 1983; Ryan, 1969; Thomas & Jones, 1970). We looked for spikes in the keystroke latency serial position function to locate where chunk boundaries might lie. The spike in latency could simply reflect a grouping strategy—it does not necessarily imply that participants are forming a chunked representation of the group of letters. Thus, we used the observed grouping strategy to derive transfer predictions for Experiment 3. If the group of letters is being represented as a chunk, then transfer should be observed to new sequences that share the group of letters. If the transfer predictions of the grouping strategy match the observed transfer pattern, then it is possible that chunks produced the transfer effects seen in Experiment 3.

The latency serial position functions are shown for the training portions of each experiment in Figure 11. There is remarkable consistency in the shape of this function across experiments and sequence types: All functions have spikes at the first and fourth positions, consistent with typists parsing the sequences into two three-letter groups (trigrams). Participants were clearly grouping the letters, and the grouping strategy used for each sequence type was the same.

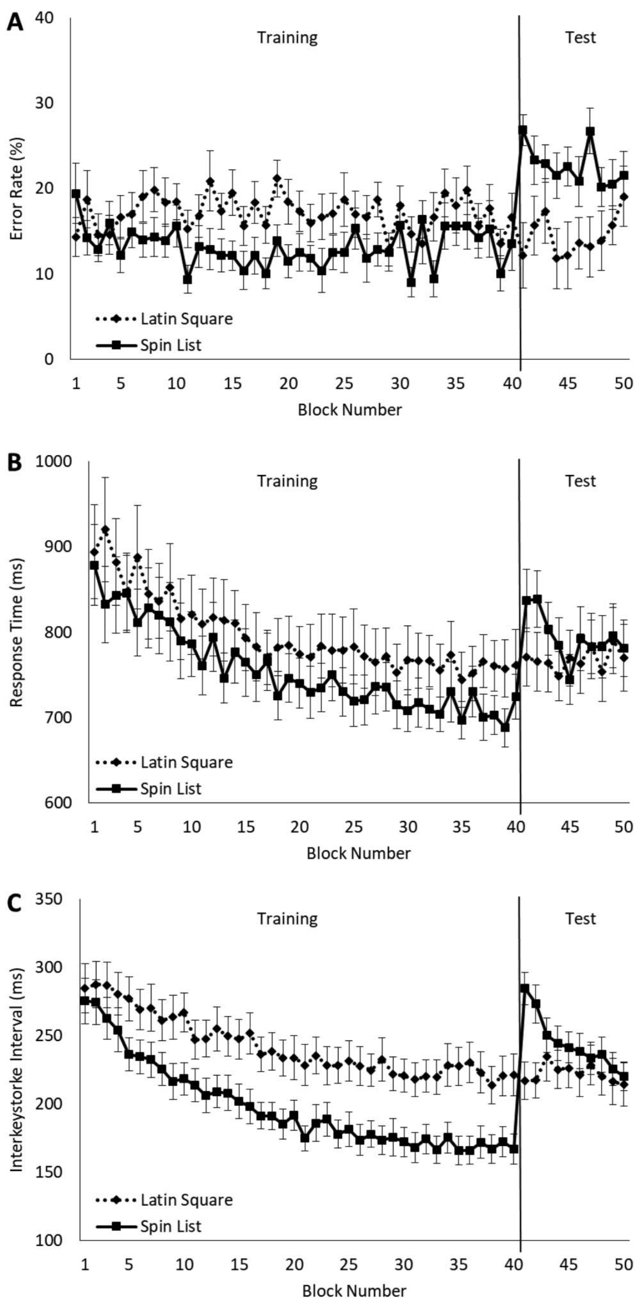

Figure 9. Experiment 4: Mean error rate (Panel A), response time (Panel B), and interkeystroke interval (Panel C) for each sequence type as a function of experiment block. Participants practiced training sequences in blocks 1 through 40 and test sequences in blocks 41 through 50. The bars are standard errors of the means.

If participants formed chunked representations based on their grouping strategy, then we would expect to see a transfer pattern like Panel C of Figure 5. Grouping the letters into threes splits the sequence in half, potentially forming two chunks. Transfer would be observed to sequences that share one or more of the chunks. Transfer would be greatest to the same sequence (which shares both chunks), second greatest for sequences with the highest magnitude spin (spin ±3; which also share both chunks but lose the support of whole-sequence representations), and lowest for the remaining sequences (which share only one of the two chunks). Compared with the predictions of item-to-item associations, trigram chunking predicts superior performance for spin ±3 sequences. We conducted contrast analyses to test the predictions of trigram chunking, using contrast weights of 1, 1, 1, 1, and −4 to sequences of spin −2, spin −1, spin +1, spin +2, and spin +3, respectively. Like the contrasts analyses for the sequence similarity predictions, the contrast analyses for chunking support no transfer differences among spun sequences (see Table 9). Participants were grouping the letters, but it does not seem that they were creating chunked representations of the letters.[1]

The lack of chunking in the current study is seemingly at odds with Yamaguchi and Logan (2016), who concluded that typists chunked the letters in nonwords over practice. They also defined chunks operationally, as better recall of a list of digits concurrently stored in memory. Better digit recall over practice does not necessarily imply that chunks are being formed over practice. Participants might learn to offload letters onto long-term memory (cf. Servant, Cassey, Woodman, & Logan, 2017), storing only the first few letters in working memory and using associations to later letters to retrieve the remainder of the sequence. Chunking may play little role in the typing of unfamiliar sequences. Alternatively, it may be the case that chunks are formed only when the sequence is stored in working memory. In Yamaguchi and Logan's experiments, participants had to store the nonword sequences they typed in working memory, whereas our participants did not.

Neither position-to-item associations nor sequence representations account for the spin list learning advantage. Neither chunking nor sequence similarity account for our transfer findings. The only remaining viable explanation is that item-to-item associations play a role in typing. To the extent that the spin list learning advantage and bigram frequency effects are comparable, bigram frequency effects in typing should also be at least partially attributable to item-to-item associations.

Simple Cues or Compound Cues?

In typing, each letter is potentially associated with several other letters. If memory is cued with an individual letter, retrieval of the proper letter might be hindered by the letter's several other associations. This interference problem is shared more generally with any associative chaining theory with simple cues—that is, any theory that assumes that individual items are the retrieval cue (Lashley, 1951). To resolve this interference, more complex associative chaining theories introduced compound cues that are composed of each previously retrieved item (Elman, 1990; Howard & Kahana, 2002; Jordan, 1986; Murdock, 1995). Increasing the complexity of the cue reduces the number of interfering associations. The words *pat* and *tap*

[1] Although we described chunks as hierarchical structures, our conclusions about chunking are not contingent upon this assumption. Regardless of the assumed representational structure, chunks have boundaries, these boundaries lead to certain operational characteristics, and our conclusions are based upon these characteristics.

Table 11
Experiment 4: ANOVA and Simple Main Effect Analyses for Training and Transfer Effects

DV and type	F	dfs	MSE	p	ϵ	η_p^2
Error rate						
Spin vs. Latin square	28.968	1,23	.026	<.001	1.000	.557
Type × Presentation	0.910	39, 897	.010	.629	.838	.038
Presentation (spin)	1.206	39, 897	.010	.184	.648	.050
Presentation (Latin square)	0.979	39, 897	.010	.508	.948	.041
Start portion (spin)	47.246	1, 23	.016	<.001	1.000	.673
End portion (spin)	55.610	1, 23	.018	<.001	1.000	.707
RT						
Spin vs. Latin square	8.299	1, 23	99,759	.008	1.000	.265
Type × Presentation	1.066	39, 897	4,079	.363	.515	.044
Presentation (spin)	13.497	39, 897	4,079	<.001	.220	.370
Presentation (Latin square)	11.200	39, 897	4,079	<.001	.197	.327
Start portion (spin)	12.180	1, 23	9,102	.002	1.000	.346
End portion (spin)	79.399	1, 23	10,639	<.001	1.000	.775
IKSI						
Spin vs. Latin square	18.860	1, 23	50,888	<.001	1.000	.451
Type × Presentation	3.083	39, 897	503	<.001	.580	.118
Presentation (spin)	46.489	39, 897	503	<.001	.308	.669
Presentation (Latin square)	22.632	39, 897	503	<.001	.340	.496
Start portion (spin)	0.103	1, 23	3,465	.751	1.000	.004
End portion (spin)	270	1, 23	2,518	<.001	1.000	.922

Note. "Presentation" analyses only include the 40 training blocks. "Start portion" and "End portion" analyses compare the 6 test blocks to the first 6 blocks and last 6 blocks of training, respectively. DV = dependent variable; RT = response time; IKSI = interkeystroke interval; ANOVA = analysis of variance.

share the same letters but would not share any compound cues or associations: In *pat* the cues are *p* and *pa*; in *tap* they are *t* and *ta*. Compound cues and their associations should only be shared between sequences that share runs of items (e.g., *wood* and *wool*, which share the run *woo*).

Spin list sequences shared letter pairs and runs of letters, so they permitted the formation of associations between simple cues and items and between compound cues and items. However, the transfer predictions of compound cues differ qualitatively from the predictions of simple cues. If compound cues are formed, training on the sequence *tpgubk* leads to learning of 5 compound cues: *t*, *tp*, *tpg*, *tpgu*, and *tpgub*. Positive transfer would be expected to unlearned sequences that share these cues. Different spins of the sequence produced different runs of letters, so different spins had different numbers of overlapping cues. Compound cues, unlike simple cues, predict transfer that is sensitive to spin distance. We found transfer that was insensitive to spin in Experiment 3. At least in unskilled typing, simple cues are used, not compound cues.

Implications for Skilled Typing and Beyond

It is noteworthy that our implementation of spin list sequences minimized the amount of associative inference between letters. Each letter was only strongly associated to two other letters (the letter that comes before it and after it in the sequence). Everyday typing does not share this feature, so the current results need not imply that item-to-item associations play a significant role in skilled typing (e.g., Logan, in press; Rumelhart & Norman, 1982). Future research will need to

Table 12
Experiment 4: The t Tests for First Block Performance and Interaction Contrasts

DV and test (A vs. B)	t	df	$M_{\text{A-B}}$	$SE_{\text{A-B}}$	p	d	BF
Error rate							
SB1 vs. LB1	1.279	23	0.052	0.040	.214	0.261	2.257 (N)
Contrast	3.191	23	3.638	1.140	.002	0.651	10.394 (A)
RT							
SB1 vs. LB1	−0.692	23	−15.572	22.497	.496	−0.141	3.749 (N)
Contrast	1.426	23	1,038.331	728.158	.084	0.291	1.906 (N)
IKSI							
SB1 vs. LB1	−0.794	23	−9.311	11.721	.435	−0.162	3.503 (N)
Contrast	5.538	23	1,416.198	255.718	<.001	1.130	1,784.352 (A)

Note. For Bayes factors (BF), numbers followed by (A) indicate evidence in favor of the alternative hypothesis, and numbers followed by (N) indicate evidence in favor of the null hypothesis. SB1 = Spin list, Block 1 of training; LB1 = Latin square, Block 1 of training; DV = dependent variable; RT = response time; IKSI = interkeystroke interval.

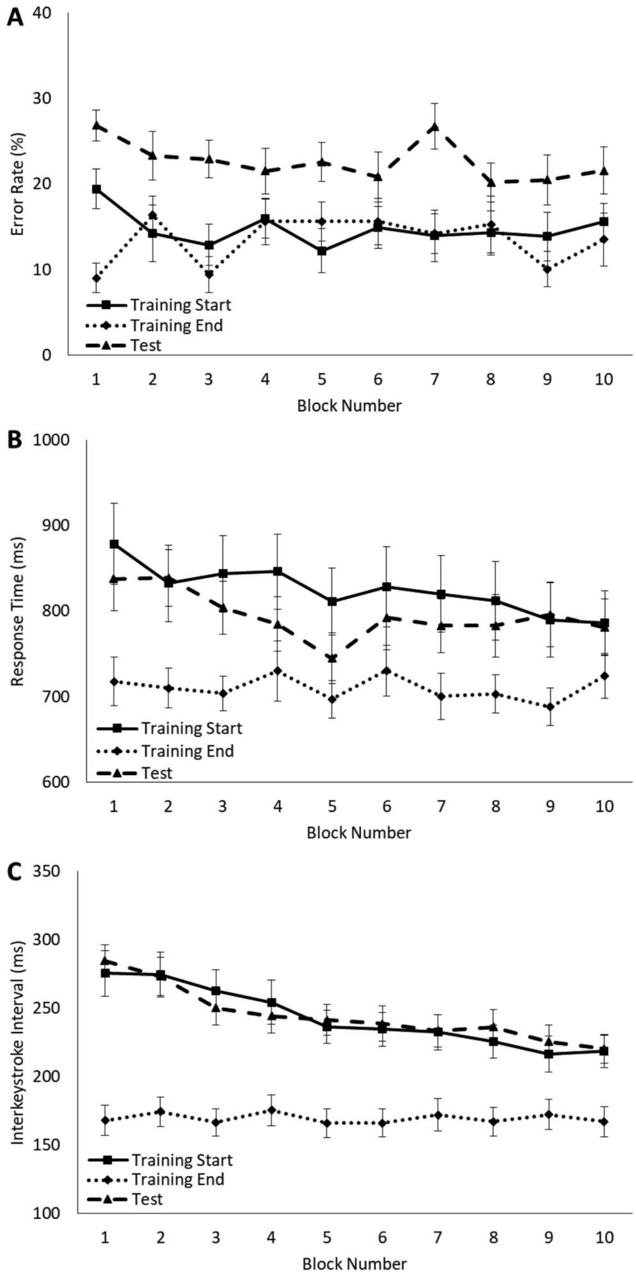

Figure 10. Experiment 4: Mean error rate (Panel A), response time (Panel B), and interkeystroke interval (Panel C) for training portion and test portion (reversed training portion) sequences as a function of the presentation number of the sequence. The bars are standard errors of the means.

determine whether item-to-item associations play a role in skilled typing. However, the present results suggest that item-to-item associations may play a role in typing skill more generally. A broader theoretical account of typing that incorporates novice performance and the development of performance over practice will need to contend with our findings.

Our experiments bear similarities to tasks typically used in the implicit serial learning literature. In the serial RT task, for example, participants have to respond individually to each item in a novel sequence, and responses become quicker to the items in the sequence as it is practiced (Nissen & Bullemer, 1987). Consistent with our conclusions, it is generally well-accepted that associations are formed between sequence elements (e.g., Cohen, Ivry, & Keele, 1990; Schuck et al., 2012). Unlike our task design, participants in serial RT tasks must learn novel stimulus-response mappings and typically (but not always, see Schuck et al., 2012) respond to a long continuous stream of stimuli. Participants did not need to learn new response mappings in our experiments, so our design allows us to rule out any influence of stimulus–response associations. The list structure we employed allowed us to make novel transfer predictions (Experiment 3) and also makes our experiments comparable to serial memory tasks, which tend to use list presentation as well.

Under similar conditions of minimal associative interference, serial recall patterns are consistent with the predictions of associative chaining theories (Kahana, Mollison, & Addis, 2010; Solway et al., 2012). It is possible that item-to-item associations are useful in any task where these associations are not rendered ineffective by associative interference. In typing, and in tasks more broadly, item-to-item associations are just one source of information on which a person can rely (see also Caplan, 2015; Kahana et al., 2010). These associations are not sufficient—we are not calling for a return to associative chaining. However, we believe that theories of serial order may ultimately need to reincorporate item-to-item associations.

Remaining Questions

Our results suggest that typing makes use of item-to-item associations, but it is currently not clear where in the stream of processing the item-to-item associations are being formed. They could be formed between perceptual representations of the letters in the display, phonological representations of the letters in working memory, or motor commands in the motor system (for similar discussions in implicit serial learning, see Abrahamse, Jiménez, Verwey, & Clegg, 2010; Fendrich, Healy, & Bourne, 1991). The disparate IKSI and RT results give some clues about their locus. IKSI reflect the time to make keystrokes. RT, while also encompassing the time to make the first keystroke, largely reflect the time to perceive the sequence. The associations that are formed improve keystroke execution, but not sequence perception. It seems that the associations are not between perceptual representations of the letters. Rather, they seem to be formed between representations in working memory or—more likely, given that the sequences did not need to be held in working memory—between representations in the motor system. However, we cannot confidently locate these associations in the current experiments because letters had just one corresponding stimulus and one corresponding response. Changing the order of letters in the display necessarily cascaded, producing corresponding changes to phonological representations and motor responses. To better answer this question, we would have needed to dissociate the perceptual, phonological, and motoric representations of the items in the sequence.

It is also unclear to what extent our results rely on participants explicitly learning the structure of spin lists. After detect-

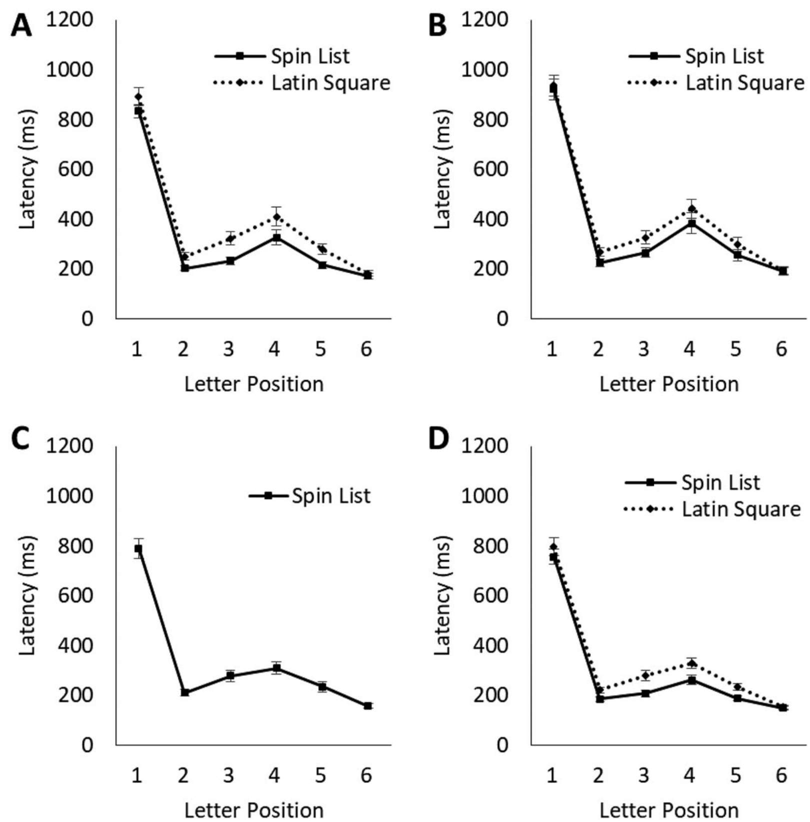

Figure 11. Mean time to initiate a keystroke in the training portion, shown as a function of letter position. Panel A: Experiment 1; Panel B: Experiment 2; Panel C: Experiment 3; Panel D: Experiment 4. The bars are standard errors of the means.

ing the spin of the sequence, participants might execute the sequence with respect to the previous learning episode ("this is same as the last sequence, but it begins at the second position with the letter *t* in the first position"). It would be important to see whether our results can be obtained even when the structure of spin lists is not detected (cf. Yamaguchi & Logan, 2016).

Conclusion

In the current study, we asked whether item-to-item associations are used in typing. Using a variant of Ebenholtz's (1963) spin list learning procedure, we demonstrated that item-to-item associations are used in typing. We also qualified these associations: they are asymmetric associations between pairs of individual letters. We believe it is necessary, but not sufficient, to include these associations in a general theory of typing.

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