Implicitly-learned spatial attention is unimpaired in patients with Parkinson’s disease

Caitlin A. Sisk¹
Emily L. Twedell¹²
Wilma Koutstaal¹
Scott E. Cooper²
Yuhong V. Jiang¹

¹ Department of Psychology, University of Minnesota
² Department of Neurology, University of Minnesota

Abstract
Extensive research has examined how current goals influence spatial attention. Yet the allocation of spatial attention is also guided by previous experience, which may induce consistent spatial preferences when a visual search target is frequently found in one region of space. Here, we examined the role of the dopaminergic system in acquiring and maintaining location probability learning. We tested Parkinson’s patients and age-matched controls in a difficult visual search task in two sessions. In Session 1, unbeknownst to the participants, the target appeared most often in one quadrant in an early, training phase of the experiment. The target was randomly located in a later, testing phase. Both Parkinson’s patients and controls acquired an attentional preference toward the high-probability quadrant during training that persisted in the testing phase. Learning yielded a large reduction in response time (345 ms) in Parkinson’s patients, and this effect was highly significant. In Session 2, administered several days later, the target’s high-probability quadrant changed. Both groups acquired a new preference for Session 2’s high-probability quadrant, demonstrating reversal learning. These findings contrast with previously observed deficits in PD in acquiring probabilistic learning and contextual cueing. This result suggests that not all habit-like behaviors depend on the basal ganglia and the dopaminergic system. Instead, preservation of location probability learning may compensate for other types of attentional deficits in PD.

Keywords: Visual Attention, Basal Ganglia, Location Probability Learning, Parkinson’s Disease

1. Introduction
Humans live in an increasingly complex sensory-spatial environment, in which information overload poses challenges to such varied activities as driving, spatial navigation, and classroom learning. One fundamental mechanism for reducing information overload is to selectively process information from important spatial locations. Decades of research demonstrate that people can prioritize particular locations based on task goals and perceptual salience (Egeth & Yantis, 1997). However, recent work using visual search and other paradigms highlights the role of learning through experience in shaping spatial selection.

In a visual search task, spatial locations that frequently contain a target are preferentially attended -- even when people are unaware of the target’s most likely location (Druker & Anderson, 2010; Geng & Behrmann, 2002; Jiang, Swallow, Rosenbaum, & Herzig, 2013; Miller, 1988). Unlike goal-driven attention, this form of attention is unimpaired by the imposition of a secondary working memory load or by cognitive aging (Twedell, Koutstaal, & Jiang, 2017; Won & Jiang, 2015). Its preservation in hemifield neglect patients (Geng & Behrmann, 2002; Shaqiri &
Anderson, 2012) suggests that the underlying mechanism of location probability learning is largely independent of frontoparietal regions. However, the contribution of subcortical regions involved in the control of spatial attention, particularly the basal ganglia, is unknown. To gain an understanding of the neural correlates of location probability learning, here we tested individuals who have known impairment in basal ganglia function: persons with Parkinson's disease.

Parkinson’s disease (PD) is a common progressive neurodegenerative disease involving the basal ganglia with a lifetime occurrence rate of about 2% (Elbaz et al., 2002). In PD, loss of dopaminergic neurons in the substantia nigra – the basal ganglia origin of the nigrostriatal dopaminergic system – results in debilitating motor symptoms. The extensive connections between the dorsal striatum and cortical regions also result in cognitive deficits in PD, including executive dysfunction (Gotham, Brown, & Marsden, 1988; Owen et al., 1993; for meta-analytic summary, see Kudlicka, Clare, & Hindle, 2011) and difficulty in acquiring probabilistic learning (Knowlton, Mangels, & Squire, 1996; Siegert, Taylor, Weatherall, & Abernethy, 2006; Witt, Nuhsman, & Deuschl, 2002a). Although the impact of PD goes beyond the nigrostriatal dopaminergic system, PD has been a useful model for understanding the function of this system.

Individuals with PD experience attentional problems in complex tasks. When driving through an urban area, Parkinson’s patients more often miss important landmarks and road signs than do healthy controls (Uc et al., 2006). In contrast, laboratory studies using standard attention tasks such as visual search and spatial cueing have not consistently revealed impairments in Parkinson’s patients (Horowitz, Choi, Horvitz, Côté, & Mangels, 2006; Zhou et al., 2012). Yet, notably, learning is rarely a component of laboratory attention tasks. It is possible that attention problems in PD arise specifically from probabilistic learning. If so, unlike individuals with other neurological conditions, such as hemifield neglect, patients with PD may be impaired in location probability learning. Indeed, as reviewed next, several lines of work suggest that such impairment may exist in PD.

First, early studies using a “weather prediction task” suggest that Parkinson’s patients may be impaired in probabilistic learning. In a classic study, Knowlton and colleagues reported a double dissociation between Parkinson’s patients and amnesic patients in impaired probabilistic learning and declarative memory, respectively (Knowlton et al., 1996). In the weather prediction task, four geometric shapes are each probabilistically associated with a weather forecast. For example, triangles may predict rain 75% of the time, and rectangles may predict sun 57% of the time. On each trial, participants use a subset of cards with these shapes to predict the weather. They are not informed of the probabilistic association and instead learn about the plausible outcomes through trial-and-error. Despite their lack of declarative knowledge, amnesic patients learned as quickly as controls in the first 50 trials. In contrast, Parkinson’s patients showed the opposite pattern -- intact declarative memory but impaired probabilistic learning (see also Witt, Nuhsman, & Deuschl, 2002a). In addition, neuroimaging studies have shown increased activation in the basal ganglia when healthy adults perform the weather prediction task, implicating this region in probabilistic learning (Poldrack et al., 2001). Performance on another task that involves implicit probabilistic learning – a serial reaction time task – is also reduced in Parkinson’s patients (Siegert et al., 2006). These findings raise the possibility that probabilistic learning, including that underlying implicit guidance of spatial attention, is impaired in Parkinson’s patients.

A second reason to hypothesize that Parkinson’s patients may be impaired in location probability learning derives from a related (though distinct) phenomenon -- the visuospatial learning effect known as contextual cueing. Participants in van Asselen et al. (2009) searched for
a letter target among letter distractors. Some search displays were repeated, and these repeated displays were randomly interspersed with unrepeated displays. Despite a lack of declarative knowledge about display repetition, healthy controls found the target faster in repeated displays than unrepeated ones. In contrast, Parkinson’s patients showed no contextual cueing. Van Asselen et al. (2009; see also van Asselen et al., 2012) related this finding to the role of the basal ganglia and the nigrostriatal dopaminergic system in implicit learning. More recent studies have implicated the basal ganglia in affecting the probability of saccades toward particular locations (Hikosaka, Kim, Yasuda, & Yamamoto, 2014). Ferrante, Di Caro, Della Libera, Santandrea, and Chelazzi (2018) suggest that the basal ganglia may be involved in the use of target and distractor location probabilities to guide spatial attention and to form habitual attention. This proposal is consistent with the broader view of basal ganglia as being critical for forming and maintaining habitual behaviors (Graybiel, 2008; Redgrave et al., 2010).

However, not all studies support the view that probabilistically guided spatial attention may be impaired in PD. First, implicit learning is preserved in PD in some paradigms, including artificial grammar learning (Reber & Squire, 1999; Witt, Nühsman, & Deuschl, 2002b). Other research has found preserved serial reaction time learning in PD (Smith, Siegert, McDowall, & Abernethy, 2001). Further scrutiny of findings from the weather prediction task also suggests that there may be alternative explanations for PD’s performance on this task. Moody, Bookheimer, Vanek, and Knowlton (2004) reported no behavioral deficit in the PD group on this task. Other studies reported a learning deficit only when patients were on dopamine-replacement medication (Jahanshahi et al., 2010; Speekenbrink, Lagnado, Wilkinson, Jahanshahi, & Shanks, 2010). Furthermore, an analysis of the various possible learning strategies involved in the weather prediction task complicates theoretical interpretation. To improve performance on the task, a participant may rely on the learning of the additive probabilistic associations of multiple cards or, instead, they may just rely on the probabilistically dominant card. Both strategies can yield high accuracy. Whereas healthy controls shift from using a single-cue (dominant card) to using multiple-cues (additive probabilities of multiple cards), Parkinson’s patients retain single-cue strategies throughout the task (Shohamy, Myers, Onlaor, & Gluck, 2004). These findings raise doubts regarding whether Parkinson’s patients are indeed impaired in probabilistic learning.

Furthermore, even visuospatial tasks that show deficient performance in Parkinson’s patients -- contextual cueing -- may not tap into probabilistic learning, van Asselen et al. (2009) did not report the medication status of the Parkinson’s patients, making it unclear whether impairment in contextual cueing is due to dopamine deprivation (in patients tested off-medication) or dopamine overdose (in patients tested on medication). The extent of the inferences that can be drawn from this contextual cueing task are limited not only because of the uncertainty regarding the contribution of dopaminergic medication to these findings, but also because the task does not involve probabilistic learning of the target’s location probability. In contextual cueing, the repeated displays each use a different target location, preventing acquisition of a spatial preference for a certain area. In addition, repeated and novel displays share the same target locations, eliminating any advantage of a learned preference for spatial areas. Contextual cueing thus depends on learning specific spatial configurations of repeated displays. A deficit in contextual cueing could arise from impairments in context learning, rather than from impaired probabilistic learning.

To address these inconsistencies and contradictory predictions, here we tested Parkinson’s patients in a location probability learning task. In this task, participants visually search for a target among multiple distractors on a computer screen. Unbeknownst to them, the target appears more often in some locations than others across multiple trials. We examined
whether Parkinson’s patients could rely on the target’s location probability to optimize spatial attention.

Location probability learning is an ideal paradigm for understanding probabilistically learned attention. Like other probabilistic learning tasks, location probability learning is acquired gradually (Salovich, Remington, & Jiang, 2017). Like many habitual behaviors, once acquired, the attentional preference persists beyond the period in which it is reinforced (Jiang et al., 2013). Adding a secondary task does not impair location probability learning, demonstrating automaticity (Won & Jiang, 2015). Because of these shared characteristics with habitual behavior, some studies have linked location probability learning to the formation of a “search habit” (Ferrante et al., 2018; Salovich et al., 2017; see also Seger, 2018). Collectively, these observations raise questions about the capacity for this type of attention in Parkinson’s patients.

Participants in our study completed two experimental sessions, separated by approximately one week. In both sessions, they searched for a letter T (the target) among letter Ls (distractors). Within each session, target location was biased toward a high-probability quadrant in an initial training phase and was random (i.e., equally probable across all quadrants) in a subsequent testing phase. This allowed us to examine both the initial acquisition of location probability learning and its persistence during the unbiased testing phase. The second experimental session also consisted of a training phase followed by a testing phase. However, in the training phase of the second session, the high-probability quadrant was different than that of the first session (see Figure 1). Changing the location of the high-probability quadrant during the training phase of the second experimental session allowed us to probe reversal learning. That is, we could determine whether the previously-learned high-probability location from a week earlier influenced acquisition of probability-based search bias toward the new high-probability locations. Because we were interested in the effects of impaired dopaminergic function, and because we wished to avoid potentially confounding effects of medication, all Parkinson’s patients were tested while off their usual dopamine-replacement medication. This design allows us to assess, for the first time, whether Parkinson’s patients are impaired in probabilistic learning in spatial attention.

![Figure 1](image.png)

**Figure 1.** Left. A sample visual search display. Participants search for the T target and report its color. Items were either red (illustrated here in black) or green (illustrated here in white), displayed on a black background. Middle: The target’s location probability in Session 1. It is biased toward one quadrant in the training phase (blocks 1-8) and unbiased in the testing phase (blocks 9-12). Right: The target’s location probability in Session 2, administered about 1-week later. The target is biased toward a new quadrant during the training phase, the “Session2-high” probability quadrant. Its location is unbiased in the testing phase.

2. Method
2.1 Participants.

Twelve Parkinson’s patients and 24 age-matched healthy controls completed this study. A neurologist referred participants with PD. Healthy controls were recruited from local
communities. An initial phone screening determined eligibility. All participants had normal or corrected-to-normal vision and hearing, normal color vision, no history of neurological disorders (besides PD in the PD group), no history of serious health problems such as uncontrolled diabetes, were native English speakers, and had completed elementary school. All participants provided written informed consent and were compensated for their time. The study protocol was approved by the University of Minnesota’s IRB. Two in-person visits were scheduled approximately one week apart. In the event that a participant could not return within one week, we scheduled a control participant using the same lag.

2.2 Power.

The sample size here is comparable to previous studies testing neurological patients on location probability learning tasks. For instance, Shaqiri and Anderson (2012) compared 11 hemifield neglect patients with five controls in a location probability learning task. This sample size is adequate because location probability learning is a large effect, with Cohen’s $d$ ranging from 1.91 to 2.68 in Experiment 1 of Jiang et al. (2013). Power to detect this effect exceeds 95% with a sample size of 12. Replicability is further bolstered by the design of the current study. Testing participants in two sessions provides an index of consistency between sessions.

2.3 Assessment.

During the first visit, participants completed assessments of cognitive processing and disease severity before completing the visual search task. Specifically, a Mini-Mental State Exam (MMSE) was administered, on which all participants scored 29 or 30. In addition, the vocabulary and abstraction sections of the Shipley Institute of Living Scale-2 (Shipley-2; http://www.creativeorgdesign.com) were administered to obtain standardized IQ. For Parkinson’s patients, a certified researcher conducted the Movement Disorder Society Unified Parkinson’s Disease Rating Scale (MDS-UPDRS), including a rating of the Hoehn and Yahr Stage. Further demographic information was collected as well, including handedness and the side of greater disease severity in PD. Three control participants were left-handed, and all other participants were right-handed. For patients, five reported greater severity on the right side, four reported greater severity on the left side, one initially noticed symptoms on the left side but reported greater severity on the right side at the time of testing, and the remaining two did not report greater severity on one side or the other. Table 1 lists scores on several of these measures and additional demographic information.

<table>
<thead>
<tr>
<th>Table 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographic information and mean scores on assessment tests for Parkinson’s patients (PD) and healthy controls. Standard error of the mean is in parentheses.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Group</th>
<th>Gender Dist.</th>
<th>Age (years)</th>
<th>Shipley Vocabulary</th>
<th>Shipley Abstraction</th>
<th>MMSE</th>
<th>Days b/w Sessions</th>
<th>Hoehn &amp; Yahr</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td>8 M; 4 F</td>
<td>61.3 (3.2)</td>
<td>103.2 (2.5)</td>
<td>98.6 (3.7)</td>
<td>29.9 (0.08)</td>
<td>7.5</td>
<td>21 (0.3)</td>
</tr>
<tr>
<td>Control</td>
<td>9 M; 15 F</td>
<td>62.6 (1.6)</td>
<td>109.5 (2.0)</td>
<td>109.0 (1.9)**</td>
<td>29.9 (0.06)</td>
<td>8.0</td>
<td></td>
</tr>
</tbody>
</table>
Note. Gender Dist.: Gender distribution; MMSE: Mini-Mental State Exam score. Days b/w sessions: median number of days between the first and second sessions. **: \( p = 0.01 \). All measures were statistically equivalent between the two groups, except for the Shipley Abstraction score which was significantly lower in the PD group.

Parkinson’s patients ceased regular L-dopa or other dopamine-replacement medication starting at 8pm the night before each in-person experimental session. All parts of the study were completed at least twelve hours after cessation of medication. Those patients with deep brain stimulation (DBS; \( N=4 \)) turned off their device upon arriving for each visit. These participants did not begin the visual search task or the UPDRS until the DBS had been turned off for at least one hour. This has been shown to be an appropriate washout period for eliminating residual effects of the DBS (Cooper, McIntyre, Fernandez, & Vitek, 2013; Temperli et al., 2003).

2.4 Materials and Task.

Participants were tested individually in a quiet room with normal interior lighting. The search task was written in MATLAB and Psychtoolbox (Brainard, 1997; Pelli, 1997) and displayed on a 15” laptop. Viewing distance was unconstrained (approximately 40cm). On each trial, participants searched for a single T target among a varying number of L distractors (7, 11, or 15). Each item was \( 2° \times 2° \) in size and rotated randomly. The item locations were randomly selected from 100 possible locations \( (10 \times 10; 32° \times 32°) \). A white frame \( (39° \times 39°, \text{width } 0.2°) \) encompassed the search space. Items were presented against a black background. The search items were predominantly white with a red or green tint. The RGB values were \([250 \ 188 \ 188]\) for red and \([188 \ 250 \ 188]\) for green. Luminance and CIE values of the colors were as follows: red: \( x = 0.3645, \ y = 0.3325, \ \text{luminance} = 83.66 \ \text{cd/m}^2 \); green: \( x = 0.3145, \ y = 0.4021, \ \text{luminance} = 125.0 \ \text{cd/m}^2 \). To begin each trial, participants were required to click a fixation square \( (1° \times 1°) \) using the mouse. The location of the square was jittered between each trial within \( 2.5° \) of the center of the screen. The requirement for hand-eye coordination ensured central fixation at the start of each trial. The fixation square remained on the screen until the participant clicked on it. The search display appeared 200 ms after the offset of the fixation square. Participants were instructed to find the T and press the \( r \) key on the keyboard if it was tinted red and \( g \) if it was tinted green. Though not instructed to, most participants used their right hand to click the fixation square and their left hand to make the keyboard response in the search task. The search display remained visible until participants made a response. Instructions emphasized both speed and accuracy of response. Target color was randomly determined with the constraint that the two colors occurred equally often in each block.

2.5 Experimental Design.

The visual search tasks were identical between Session 1 and Session 2, unless noted. First, participants completed 17 practice trials, in which the target location was randomly selected from 100 possible locations. Next, participants completed 12 experimental blocks, each containing 36 trials. Blocks 1-8 comprised the training phase, in which the target appeared in a randomly selected “high-probability” quadrant in 50% of the trials. The target appeared 16.7% of the time in each of the remaining three “low-probability” quadrants. The exact location within the quadrant was randomly selected from 25 possible locations. The assignment of the high-probability quadrant was counterbalanced across participants, and the assigned high-probability quadrant was held constant throughout the training phase. Blocks 9-12 comprised the testing phase, in which the target appeared equally often in all four quadrants. Distractors were randomly distributed with the constraint that an equal number of items appeared in each quadrant on each trial. Trials of different set sizes (8, 12, or 16 items) were randomly intermixed.
To examine reversal learning, the high-probability quadrant differed between the two sessions. Session 1’s high-probability quadrant was randomly assigned and counterbalanced across participants. Session 2’s high-probability quadrant was chosen randomly from the two adjacent quadrants of Session 1’s high-probability quadrant, and this choice was also counterbalanced across participants. A second difference between the two sessions was a surprise recognition test following Session 2. In this test, participants were first asked whether they believed the target appeared more often in some places than others (phrased in general terms, with no mention of any difference between the two sessions), or whether the target appeared equally often everywhere. Regardless of their answer to this question, participants were informed that the target did appear more often in some places than others. They were asked to identify the quadrant where they thought the target most often appeared, then rate their confidence in that choice on a four-point scale ranging from one (guessing) to four (completely certain).

3. Results

Participants rarely made mistakes in the visual search task. Controls were slightly more accurate than Parkinson’s patients (99.6% vs. 99% in Session 1, \( p = .01 \); 99.7% vs. 99% in Session 2, \( p = .01 \)). However, even Parkinson’s patients were highly accurate (99%). Accuracy did not interact with the location probability manipulations, all \( F < 1 \). Because accuracy was high in both groups, we focus instead on RT as the main dependent measure.

In the RT analysis, we excluded incorrect trials and trials with RT less than 250ms (fewer than 0.1%) or more than 10,000ms (fewer than 0.7%). Because Parkinson’s patients had numerically slower RT overall, normalized RT data provide a better measure of the effects of interest (Faust, Balota, Spieler, & Ferraro, 1999). We therefore converted each trial of each participant’s RT into a z-score relative to that participant’s own mean. Both normalized RT and raw RT data are displayed in the figures.

We first report learning in terms of normalized RT across blocks, combining data from all set sizes to test for a general location probability learning effect. Subsequently we examine search efficiency across different set sizes.

3.1 Session 1: The acquisition and persistence of location probability learning.

Figure 2 shows RT data from Session 1.

Both Parkinson’s patients and healthy controls were faster when the target appeared in the high-probability quadrant than when it appeared in the low-probability quadrants. Furthermore, the normalized data from the training phase were qualitatively similar between PD and controls. An ANOVA including group (PD vs. control) as a between-subject factor and quadrant condition (high- vs. low-probability) and training block (1-8) as within-subject factors showed a main effect of quadrant, \( F(1, 34) = 111.34, p < .001 \), \( \eta_p^2 = .77 \) and block, \( F(7, 238) = 7.568, \eta_p^2 = .18 \). There was no interaction between group and quadrant condition, \( F(1, 34) = 0.35, p = .56 \). There was also no interaction between group, quadrant condition, and block, \( F(7, 238) = 1.00, p = .43 \). Parkinson’s patients were numerically slower (though this did not reach significance in the raw RT data, \( F(1, 34) = 1.75, p = .20 \)). The main effect of group was not significant given the normalization of the data, \( F(1, 34) = 0.02, p = .90 \).

Although there was no interaction between quadrant condition and group, consideration of the Parkinson’s patients as an independent group allows us to determine whether learning can occur despite the neurological damage due to PD. An ANOVA including target quadrant (high-probability vs. low-probability) and training block (blocks 1-8) as factors on the normalized RT data from the Parkinson’s patients revealed significant main effects of
quadrant, $F(1, 11) = 60.75, p < .001, \eta^2_p = .85$, and block, $F(7, 77) = 3.59, p = .002, \eta^2_p = .25$. The interaction between quadrant and block was not significant, $F(7, 77) = 1.09, p = .38$. Evidently, Parkinson’s patients acquired a clear attentional preference toward the high-probability quadrant in the training phase — on average, they responded to targets in the high-probability quadrant 345 ms faster than to targets found in the other three quadrants.

![Figure 2](image)

**Figure 2.** Results from Session 1’s visual search task, presented both in the normalized reaction time (RT) form (upper panel) and in the raw RT form (lower panel). Error bars show ±1 S.E. of the mean difference between the high- and low-probability quadrants. Some error bars may be too small to see.

Once acquired, the habit of preferentially searching the high-probability quadrant persisted in the testing phase, during which the target’s location was equi-probable across quadrants. The habitual bias toward the previously high-probability quadrant no longer offered an advantage. Nonetheless, Parkinson’s patients and controls continued to respond faster when the target appeared there. An ANOVA including group (PD vs. control), quadrant condition, and block revealed no interaction between group and other factors, all $Fs < 1$. The main effect of group was not significant, $F < 1 (F(1, 34) = 2.75, p = .11$ in the raw data). This shows that the persistence of the habitual attentional preference for the previously high-probability quadrant is not significantly different between Parkinson’s patients and healthy controls.

Furthermore, when considered independently, Parkinson’s patients showed persistence of the learning. An ANOVA including quadrant condition (previously high- vs. low-probability) and testing block (9-12) on the testing phase normalized RTs of the PD group showed a significant main effect of quadrant, $F(1, 11) = 5.05, p = .046, \eta^2 = .32$, but not block, $F < 1$. This effect did not diminish significantly across the four testing blocks, resulting in a lack of
significant interaction between quadrant and block, $F < 1$. An analysis on the raw RT replicated the pattern of results reported above.

3.2. Inter-trial location repetition priming.

Might faster RT in the high-probability quadrant originate from short-term, inter-trial repetition priming? In inter-trial location priming, search time is faster if the target repeats its location across successive trials (Maljkovic & Nakayama, 1996). This effect is short-lived: it is strongest for adjacent trials, and rapidly dissipates over the next 5-8 trials. In our task, when the target appears in one quadrant disproportionately often, quadrant repetition across consecutive trials occurs disproportionately often in that high-probability quadrant. Note that inter-trial priming cannot account for data in the testing phase. In that phase, the target’s location is equiprobable in all quadrants, eliminating the disproportionate inter-trial location repetitions. Yet the search advantage persisted for over 100 trials.

To examine the contribution of inter-trial location repetition priming to the training phase data, we coded each trial as either a “repeat” or “nonrepeat” relative to the preceding trial’s target quadrant. We found clear evidence of location probability learning even on nonrepeat trials. Figure 3 shows the difference in reaction time (both normalized and raw) between high- and low-probability probability quadrants in nonrepeat trials in Session 1, plotted separately for each group. An ANOVA on normalized RT including group (PD vs. control) and quadrant (high-probability vs. low-probability) as factors found a main effect of quadrant, $F(1, 34) = 27.83, p < .001, \eta^2 = .45$, but no interaction between group and quadrant, $F < 1$.

![Figure 3](image.png)

Figure 3. Plotted here are mean normalized reaction time (RT; left) and mean raw RT (right) for nonrepeat trials to targets appearing in high- and low-probability quadrants in Session 1. Error bars show ±1 S.E. of the mean difference between the high- and low-probability quadrants.

How quickly does the search advantage in the high-probability quadrant emerge? In our data, the advantage was already statistically significant by Block 1. The rapid emergence is likely attributable to inter-trial priming. A study that de-confounded inter-trial priming from long-term learning showed that it took about 50 trials of training for the long-term component to emerge (Salovich et al., 2017). In the present study, we analyzed the very first trial in which participants encountered a target in the high-probability quadrant and the first trial in which the target appeared in a low-probability quadrant (matching for set size). We found no statistical difference between them, $t(35) = 1.43$, $p = .16$, confirming that the RT difference emerged only in subsequent trials.

3.3 Session 2: Acquiring a new search habit.
Participants returned to the lab about one week later for Session 2. The design of Session 2 was similar to Session 1 —— the first eight blocks trained participants to acquire location probability learning, and the last four blocks removed any bias in the target’s location distribution to test for persistence of acquired habitual biases. Additionally, the high-probability quadrant differed between Session 1 and Session 2, allowing us to examine reversal learning, as well as persistence of the bias acquired in Session 1.

Parkinson’s patients, like healthy controls, acquired new location probability learning in Session 2 (Figure 4).

An ANOVA on the training phase normalized RTs, including group (PD vs. control), quadrant (low-probability vs. Session 2’s high-probability), and training block (1-8) as factors, revealed significant effects of quadrant, $F(1, 34) = 86.68, p < .001, \eta^2 = .72$, and block, $F(7, 238) = 5.92, p < .001, \eta^2 = .15$, and an interaction between quadrant and block, $F(7, 238) = 2.27, p = .03, \eta^2 = .06$. Group did not interact with other factors, $p \geq .21$. The main effect of group was not significant in the normalized data, but was significant in the raw data, $F(1, 34) = 4.19, p = .048, \eta^2 = .11$, reflecting slower overall RT in Parkinson’s patients. This analysis again shows that Parkinson’s patients and controls showed the same pattern of new location probability learning.

Restricting the analysis to PD only showed significant learning in Session 2. An ANOVA on the training phase normalized RTs in the PD group, including quadrant (low-probability vs. Session 2’s high-probability), and training block (1-8) revealed significant effects of quadrant,
F(1, 11) = 52.09, p < .001, $\eta^2_p = .83$, and block, $F(7, 77) = 2.57, p = .02, \eta^2_p = .19$, and no interaction $F(7, 77) = 1.55, p = .16$. These results showed again that location probability learning is unimpaired in Parkinson's patients.

Learning acquired from Session 2's high-probability quadrant persisted in the testing phase. In blocks 9-12, an ANOVA including group, quadrant (low-probability vs. Session 2’s high-probability), and block (1-8) showed a significant main effect of quadrant, $F(1, 34) = 9.41, p = .004, \eta^2_p = .22$. The main effect of group was only present in the raw RT data, $F(1, 34) = 4.63, p = .04, \eta^2_p = .12$, and not the normalized RT data, $F < 1$. Group did not interact with other experimental factors, all $F < 1$. Thus, the pattern of within-session persistence of location probability learning was not significantly different between the PD and control groups.

Despite the approximately week-long lag between sessions, participants showed some retention of Session 1’s learning. In the training phase of Session 2, an ANOVA including group (PD vs. control), quadrant (Session 1’s high-probability vs. low-probability), and block (1-8) showed a significant main effect of quadrant, $F(1, 34) = 4.29, p = .046, \eta^2_p = .11$. RT was faster in Session 1’s high-probability quadrant than in the two consistently low-probability quadrants. This effect was numerically more apparent in Parkinson’s patients, but the interaction between group and quadrant condition was not significant, $F < 1$. No other effects were significant, $p \geq .33$. In the testing phase, an ANOVA including group, quadrant (Session 1’s high-probability vs. low-probability) and block (9-12) showed a main effect of quadrant, $F(1, 34) = 6.02, p = .02, \eta^2_p = .11$. The across-session persistence appeared to be somewhat more robust in controls, but the interaction between group and quadrant was not significant, $F(1, 34) = 1.53, p = .22$. The normalized data showed no main effect of group, $F < 1$, though the raw RT data did show a main effect of group ($F(1, 34) = 5.50, p = .03, \eta^2_p = .14$), reflecting slower RT in PD than controls. No other effects reached significance, $p \geq .30$.

In order to ensure that the observed effect was not driven by same visual field proximity, we separated participants into two groups: those whose new high-probability quadrant in Session 2 was in the same hemifield as their high-probability quadrant in Session 1, and those whose Session 2 high-probability quadrant was in the opposite hemifield as their high-probability quadrant in Session 1. We then computed the size of probability learning in the Session 2 high-probability quadrant and the retention of a bias for the Session 1 high-probability quadrant in terms of difference in average RT between the quadrant of interest and the two consistently low-probability quadrants. Hemifield relationship did not influence new learning or retention of learning, $p \geq .25$. In fact, learning in Session 2 and retention of a preference from Session 1 were both numerically greater in the different hemifield group. This suggests that same field proximity did not drive the effect observed here. Although Figure 4 appears to illustrate group differences in the manifestation of the bias for Session 1’s high-probability quadrant -- with a stronger bias in the PD group during training and in the control group during testing -- these differences did not yield significant interactions between quadrant and group. These apparent differences warrant further investigation in future studies.

Three findings emerged from Session 2. First, mirroring Session 1’s finding, PD and controls acquired new biases toward Session 2’s high-probability quadrant. Second, both groups also retained learning from Session 1. Third, both groups adapted to a change in the target’s location probability: the bias toward Session 2’s high-probability quadrant dominated over Session 1’s.

### 3.4 Search efficiency: the set size effect.

Consistent with previous reports (Horowitz et al., 2006), we found normal search efficiency in Parkinson’s patients, as measured by the slope of the linear function relating RT to
set size. Figure 5 provides search slope across the different set sizes (8, 12, 16) for Session 1. Session 2 search RT and search slope across the different set sizes are presented in Table 2.

Figure 5. Search slope from Session 1 low- and high-probability quadrants plotted separately for the two groups. Individual points represent average reaction time at each set size (8, 12, 16). Search slope for each line is included adjacent to the relevant line.

Table 2
Reaction time across set sizes in Session 2 in Parkinson’s patients (PD) and healthy controls. Standard error of the mean is in parentheses.

<table>
<thead>
<tr>
<th>Group</th>
<th>Quadrant</th>
<th>Set size = 8</th>
<th>Set size = 12</th>
<th>Set size = 16</th>
<th>Slope (ms/item)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td>Session 1 High</td>
<td>1820 (33)</td>
<td>2285 (59)</td>
<td>2544 (59)</td>
<td>90.47 (31)</td>
</tr>
<tr>
<td></td>
<td>Session 1 High</td>
<td>1667 (35)</td>
<td>1941 (37)</td>
<td>2430 (47)</td>
<td>95.33 (24)</td>
</tr>
<tr>
<td></td>
<td>Session 1 Low</td>
<td>1870 (36)</td>
<td>2305 (49)</td>
<td>2782 (62)</td>
<td>114.05 (30)</td>
</tr>
<tr>
<td>Control</td>
<td>Session 2 High</td>
<td>1558 (14)</td>
<td>1920 (19)</td>
<td>2239 (16)</td>
<td>85.01 (15)</td>
</tr>
<tr>
<td></td>
<td>Session 2 High</td>
<td>1444 (14)</td>
<td>1692 (17)</td>
<td>2089 (19)</td>
<td>80.64 (14)</td>
</tr>
<tr>
<td></td>
<td>Session 2 Low</td>
<td>1627 (14)</td>
<td>1994 (16)</td>
<td>2403 (19)</td>
<td>96.97 (14)</td>
</tr>
</tbody>
</table>

We entered set size, quadrant, and group as factors in separate ANOVAs for each session. This analysis was conducted on the raw RT data. In Session 1, RT was slower in the low-probability quadrants, $F(1, 34) = 87.86, p < .001, \eta^2_p = .72$, and at larger set sizes, $F(2, 68) = 256.38, p < .001, \eta^2_p = .88$. Search slope was shallower in the high-probability quadrant than in the low-probability quadrants, $F(2, 68) = 5.28, p = .01, \eta^2_p = .14$, suggesting that location probability learning made search more efficient. A lack of interaction between group and set size, $F < 1$, indicates similar search efficiency in PD and controls. No other effects were significant, $p \geq .18$. Session 2 presented qualitatively similar results, with shallower search slope in Session 2’s high-probability quadrant, $F(2, 68) = 7.78, p = .001, \eta^2_p = .19$, and marginally shallower search slope in Session 1’s high-probability quadrant, $F(2, 68) = 3.07, p = .05, \eta^2_p = .08,$
relative to the low-probability quadrants. The group by set size interaction was not significant, $p \geq .17$.

The slightly slower RT in Parkinson’s patients is consistent with previous studies, suggesting that motor deficits, rather than choice RT, caused the slowed response (Evarts, Teräväinen, & Calne, 1981). In addition, Parkinson’s patients and controls showed comparable search efficiency, demonstrating intact conjunction search (Horowitz et al., 2006). Both groups acquired location probability learning, manifested as faster RT and more efficient search slope in the high-probability quadrant.

3.5 Explicit awareness.

Few participants spontaneously noticed the target’s location probability manipulation. The majority (24 out of 36) said that targets were evenly distributed across the quadrants when prompted. When forced to choose the quadrant in which the target most often appeared, the number of participants who chose either the Session 1 or Session 2 high-probability quadrant did not differ from chance. In the control group, 37.5% chose a low-probability quadrant, 29.2% chose Session 1’s high-probability quadrant, and 33.3% chose Session 2’s high-probability quadrant as the target’s most frequent location. This distribution did not differ from what would be expected if participants guessed randomly, $\chi^2(2) = 1.58, p = .45$. The median confidence rating of 2 indicates low confidence in the choice. In the PD group, 33.3% chose low-probability quadrants, 16.7% chose Session 1’s high-probability, and 50% chose Session 2’s high-probability quadrant — a pattern not different from chance, $\chi^2(2) = 4.00, p = .14$. Median confidence was 2. Few participants — 8.33% of controls and 25% of PD participants — reported an uneven target distribution in the initial question and chose one of the two high-probability quadrants in the forced-choice response. Furthermore, the size of probability learning -- percent gain in RT between Session 1’s high- and low-probability quadrants -- was no greater in the nine participants who chose Session 1’s high-probability quadrant (mean percent gain = 14.8%) than for the other 27 participants (mean percent gain = 12.4% for Session 1), $t(34) = 0.74, p = .48$. Similarly, probability learning in Session 2 was no greater in the 14 participants who chose Session 2’s high-probability quadrant (mean percent gain = 8.9%) than for the other 22 participants (mean percent gain = 10.1%), $t(34) = 0.38, p = .71$. Consistent with previous studies, location probability learning proceeded via implicit, rather than goal-directed, guidance of attention.

3.6. Exploratory analysis of individual differences.

Although Parkinson’s patients in our study differed in disease severity (Hoehn & Yahr stage ranged from 1-4) and in other regards, an exploratory analysis showed that location probability learning was robust to these differences. Disease severity, as indexed by MDS-UPDRS scores, was not related to location probability learning, neither was there a relationship between learning and Shipley abstraction scores or mean RT. The strongest relationship was that between the persisting bias in Session 2 for the high-probability quadrant from Session 1 and the UPDRS score from Session 1, $r = -.54, F(1, 10) = 4.18, p = .07$. Owing to the small sample size, however, this exploratory analysis is under-powered. Future studies with a larger sample size are needed to further examine how location probability learning changes as the disease progresses.

4. Discussion

To gain an understanding of the neural basis of implicitly-learned attention, we tested Parkinson’s patients and healthy controls in a location probability learning visual search task. We found that Parkinson’s patients are unimpaired in acquiring implicitly-guided spatial
attention. Parkinson’s patients, like controls, acquired an attentional preference for locations that frequently contained a search target. The pace of acquisition and the magnitude of the effect were comparable between the two groups. Furthermore, the probability-based spatial preference persisted in an unbiased testing phase, during which the target’s location was equiprobable across all regions. When participants completed the same task approximately one week later with a different high-probability region, both Parkinson’s patients and controls acquired new location probability learning. In this second session, they also showed some evidence of retaining the previously-learned spatial preference. Not only were Parkinson’s patients unimpaired in the acquisition and retention of spatial probability learning, but they also displayed successful reversal learning.

The conclusion that location probability learning is unimpaired rests not just on a null result -- the lack of group by quadrant interaction -- but also on the equally important significant learning shown by Parkinson's patients. In Parkinson's patients, RT was significantly faster in the high-probability quadrant than in the low-probability quadrants during training. This statistically significant effect persisted through the testing phase. Furthermore, the observed significant probability learning in the PD group was found in two experimental sessions. Collectively, the significant learning in the PD group, the observation of this finding in two sessions, and the lack of a clear group by quadrant interaction suggest that location probability learning is preserved in PD.

Our results offer some important insights into the nature of the cognitive deficits in PD and the neural circuitry involved in implicitly-guided spatial attention. The deficits in PD spare at least one form of probabilistic learning: that within visuospatial attention. Because PD often impacts the basal ganglia, the unimpaired location probability learning suggests that not all probabilistic learning depends on complete, unimpaired functioning of the basal ganglia and the nigrostriatal dopaminergic system. Other proposed neuropathology of PD, including degeneration of the noradrenergic system, also appears unimportant for the type of visuospatial probability learning tested here.

This finding seemingly contradicts some previous studies. For example, van Asselen et al. (2009) observed PD-related impairments in contextual cueing, a form of implicit spatial context learning. However, this contradiction can be resolved when we consider the different mechanisms underlying these two tasks. Contextual cueing requires learning of repeated configurations and use of those configurations to guide attention. Owing to the unbiased distribution of target locations among the repeated configurations, it is impossible to acquire a consistent spatial preference in contextual cueing. In contrast, location probability learning trains people to acquire a general spatial preference independent of spatial contexts. Degeneration of brain structures critical for context learning, such as the medial temporal lobe, may impair contextual cueing without affecting location probability learning. Indeed, patients with medial temporal lobe damage are impaired in contextual cueing (Chun & Phelps, 1999). Because neurodegeneration in PD sometimes includes the medial temporal lobe (Zeighami et al., 2015), van Asselen et al. (2009)'s finding may be attributed to a deficit in spatial context learning, rather than an impairment in learning to acquire a consistent spatial bias. Location probability learning affords a stronger test of visuospatial probabilistic learning in Parkinson’s patients. As demonstrated here, they are preserved in such learning.

However, one may ask whether inter-trial repetition priming may confound our findings. Location probability learning has previously been characterized as a relatively robust form of statistical learning (Jiang et al., 2013). This characterization is consistent with the persistence of the learned preference in the testing phase. In addition, the analyses demonstrate that a bias toward the high-probability quadrant was present even in trials in which the target
appeared in a different quadrant than that in which it had appeared on the previous trial. Thus, although trial sequence effects may bootstrap long-term learning by providing important cues to the attentional system’s statistical learning machinery (Ferrante et al., 2018), location probability manipulations enable long-term learning that outlasts inter-trial priming.

Nonetheless, inter-trial repetition priming effects may be observed in the early blocks in our study, leading to the early emergence of an RT advantage in the high-probability quadrant in Block 1. This early quadrant effect does not contradict the gradual acquisition of a long-term spatial bias. In fact, a recent study demonstrated that early RT advantages in this task represent repetition priming, while the long-term statistical learning component takes time to emerge (Salovich et al., 2017). Salovich et al. (2017) intermixed short blocks of training (with a high-probability quadrant) and testing (target location equi-probable across quadrants). The testing blocks serve as a neutral probe for any long-term learning that has emerged during training. In this study, inter-trial priming was observed as soon as training began, while the long-term component, measured by persistence in the testing phase, only became significant after several training blocks. The time required for long-term location probability learning — 50-100 trials -- is similar to the exposure required for learning in the weather prediction task. In Session 1 of our study, the significant RT advantage in the high-probability quadrant in Block 1 was likely due to inter-trial priming. But as discussed above, the persistence of probability cuing in the testing phase reflected just the long-term component. Notably, the preference for the reinforced high-probability quadrant did not occur in the first block of Session 2, suggesting that the Session 1 learning overrode inter-trial priming in the first block of Session 2.

Though our study is the first to assess location probability learning in PD, previous neurological studies of location probability learning have found it to be intact in one other group of neurological patients – those with hemifield neglect. Geng and Behrmann (2002) presented a visual search target in the left half of the screen 80% of the time to participants with left hemifield neglect. Owing to their neglect syndrome, patients were faster finding the target in the right visual field. However, with training, left hemifield neglect was reduced, suggesting acquisition of a search habit toward the neglected hemifield. Two subsequent studies replicated this finding (Shaqiri & Anderson, 2012, 2013). According to the latter studies, the neglect-inducing lesions included not only parietal and frontal regions, but in several cases the basal ganglia. Shaqiri and Anderson did not separate those with and without basal ganglia damage, yet the group average suggests that location probability learning may be preserved despite basal ganglia damage. Our study provides converging evidence that the basal ganglia and the nigrostriatal system are not essential for acquiring this type of spatial probability learning. However, further lesion analysis is needed before one can confidently make this conclusion, as we cannot be completely certain that all of our Parkinson’s patients experienced impaired basal ganglia function (Rizzo et al., 2016).

Influential theories on habit learning in PD suggest that, in contrast to our results, the procedural learning involved in our task should not be intact. The habit learning hypothesis (Redgrave et al., 2010) provides an influential account for the cognitive deficits observed in Parkinson’s patients. According to this hypothesis, damage to the nigrostriatal dopaminergic system impairs acquisition and maintenance of habitual behaviors. Thus, an action that is typically automatic, such as flipping on a light switch upon entering a dark room, requires effortful control in Parkinson’s patients. The habit learning account derives from the functional dissociation between the basal ganglia on the one hand, and the medial temporal lobe and prefrontal cortex on the other. Behavioral neuroscience experiments have shown that rats trained to obtain food in a four-arm maze progress from goal-directed place learning behavior (i.e., learning where food is) to habitual response learning behavior (i.e., learning which way to
Damage to the hippocampus impairs the former whereas damage to the striatum impairs the latter (Packard & Knowlton, 2002). Given the impairment of striatal function in PD and the observed striatal-dependent habit learning in rodents, the habit learning account proposes that the cognitive deficits in PD reflect a deficient habit system. Our findings may appear to conflict with this account if the type of learning examined here reflects a search habit, as some researchers have proposed (Ferrante et al., 2018; Salovich et al., 2017).

The evaluation of the current finding in relation to the habit learning account is made difficult by the lack of a clear taxonomy, in the research literature on either human or animal learning, of habitual behaviors. Some researchers consider a broad range of behaviors to be habit-like, ranging from cigar rolling, navigation route selection, to drug addiction and compulsive behaviors (Graybiel, 2008). However, what counts as habitual in animal learning may differ from laboratory tasks administered on humans. Criteria such as automaticity and outcome devaluation could, in principle, be made comparable across species and studies (Seger & Spiering, 2011). However, behaviors that demonstrate some of those delineated properties need not rely on the same neural circuitry, making it difficult to make broad inferences from performance on one task (e.g., location probability learning) to a general theory about habits. To facilitate a discussion on the broad spectrum of automatic to habitual behaviors, here we layout several arguments that have linked location probability learning to the acquisition of a “search habit.” We then discuss mechanisms that may allow people to acquire this learning despite deficient basal ganglia function.

Previous studies have linked location probability learning to habit formation for many reasons (Ferrante et al., 2018; Jiang, 2017; Seger & Spiering, 2011; see also Seger, 2018). Learning in this task is insensitive to outcome devaluation and is unimpaired by either the concurrent imposition of secondary tasks or aging. Some studies have examined the spatial reference frame in which frequently attended locations are attended and found location probability learning to be egocentric. In these studies, the search display is placed on a tabletop, with participants looking down at the display. Participants sit at one side of the tabletop during a training phase, in which they acquire a spatial bias toward one part of the tabletop/visual field. They then move to an adjacent side of the tabletop during the testing phase, resulting in a 90° viewpoint change. Results show that as participants changed their viewpoint, the spatial preference also rotated with them, directed to the same part of the participant’s visual field rather than the same part of the tabletop (Jiang & Swallow, 2013, 2014). The egocentric coding of visual space bears similarity to response learning in animal research. Thus, location probability learning shares some features with habits.

Despite the arguments laid out above, location probability learning may be, at best, an atypical “habit.” In fact, it is unclear whether any attentional behaviors can truly be considered habitual in the same way that rituals and compulsive actions are. Nonetheless, the procedural component of spatial attention and the shared characteristics between habit learning in animal research and location probability learning make this task the closest existing analog to a search habit within the spatial attentional domain. The contrast between our findings and previous work may contribute to the development and refinement of a taxonomy for habits. Our findings may also yield important insights into the cognitive functions impaired -- or preserved -- in PD.

Consider the weather prediction task and location probability learning. Although alternative interpretations exist, the weather prediction task is sometimes associated with impaired learning in PD (Knowlton et al., 1996). Some similarities exist between location probability learning and the weather prediction task. Both involve learning of probabilistic information through visually presented stimuli. In the former, it is the spatial probability of
search target locations; in the latter, it is association of a shape with a probabilistic weather outcome. Both are predominantly implicit, and both involve trial-by-trial learning. Because Parkinson’s patients are impaired in one task but not the other, the data suggest that the core cognitive deficit resulting from PD does not lie in general probabilistic, implicit, or trial-by-trial learning. There must be some mechanisms unique to learning in the spatial attentional domain that explain these contradictory findings.

Consideration of the many differences between the tasks may elucidate these mechanisms and shed light on the core deficit underlying cognitive impairment in PD. Here, we discuss two differences that may account for the discrepant finding. First, location probability learning induces consistent spatial preferences, affecting the vector of attentional shift. This may modulate activity in the premotor system, including the superior colliculus and the frontal eye fields (Ferrante et al., 2018; Jiang, 2017). These systems may compensate for any existing deficit in the basal ganglia function assuming that the basal ganglia are affected in the participants tested here. In contrast, the weather prediction task does not induce spatial learning, depriving it of these compensatory mechanisms. On this account, the basal ganglia could be involved in location probability learning in healthy controls, but intact basal ganglia function is not essential for probabilistic learning in general.

A second difference between the tasks is the nature of feedback learning. The weather prediction task requires more informational integration -- learning depends entirely on integrating outcomes, delivered after each decision, with subsequent choices. Feedback therefore constitutes a separate step of processing from the choice itself. Location probability learning, on the other hand, has stronger inherent integration of feedback (where the target is) with the search task itself (finding the target). Paradigms analogous to location probability learning that separate reward feedback from successful search typically yield little learning. For example, if the target appears in all locations equally often, but targets found in one quadrant yield triple the monetary reward of those found in others, participants do not readily acquire an implicit attentional preference toward the highly-rewarded quadrant (Jiang, Sha, & Remington, 2015). In this reward paradigm, reception of feedback (i.e., indications of amount of money earned) is distinct from localization of the target. This disconnection changes the nature of learning. This distinction may also underlie the difference between location probability learning and the weather prediction task. On this account, the basal ganglia may be important for the kinds of probabilistic learning that require linking or chunking separate components of a task. This account is consistent with the involvement of the sensorimotor striatum in motor sequence learning but not learning of single motor responses. Single-unit recordings in non-human animals suggest that the sensorimotor striatum, the part of the striatum essential for habit formation, shows different patterns of activation for different types of learning. With extended training, sensorimotor striatum activity increased during trained sequences of movements (Miyachi, Hikosaka, & Lu, 2002). However, training of a single motor response, such as a single lever press, decreased activity in this region (Carelli, Wolske, & West, 1997). These findings are consistent with ours: not all learning depends on the basal ganglia. This idea also aligns with computational modeling of the basal ganglia, which deems chunking of separate task components an important element of basal ganglia function (Daw, Niv, & Dayan, 2005).

The importance of the observed unimpaired location probability learning in Parkinson’s patients extends beyond its contributions to our understanding of probability learning in spatial attention. The finding may offer a remedy for existing disease-related cognitive deficits. For instance, day-to-day difficulties arising from executive dysfunction may be ameliorated by careful designs of environmental conditions. Consistencies in visuospatial environments (e.g., keeping important items in consistent locations) may allow patients to take full advantage of
intact statistically-driven spatial attention, thus reducing the need for reliance on executive functions. Such tactics could improve driving performance in Parkinson’s patients. If the statistics of one’s environment, such as the locations of important stimuli (e.g., crosswalks, blind driveways), are consistent relative to the driver, they may be attended to habitually, diminishing executive demands.

In sum, this study is the first to evaluate location probability learning in patients with PD. Despite likely disruption of the nigrostriatal dopaminergic system, Parkinson’s patients were not impaired in location probability learning. This finding suggests that not all probabilistic learning is impaired in PD. Rather, probability learning in spatial attention appears to be spared. Our study suggests that implicitly-learned spatial attention is a robust mechanism for guiding visual selection. The preservation of this function in PD may help compensate for other cognitive deficits, such as executive dysfunction.

5. Funding
This work was funded by the Engdahl Family Research Fund. The funding source had no involvement in study design, data collection, analysis and interpretation of data, or the writing of the report.

6. Declaration of Interest
Declarations of interest: none.

7. Acknowledgements
We thank Jacob Guzior and Kelly Sovell for patient referral, Roger Remington for comments, and all Parkinson’s patients and volunteers for participation.

References


