



Translating visual information into action predictions: Statistical learning in action and nonaction contexts

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Abstract

Humans are sensitive to the statistical regularities in action sequences carried out by others. In the present eyetracking study, we investigated whether this sensitivity can support the prediction of upcoming actions when observing unfamiliar action sequences. In two between-subjects conditions, we examined whether observers would be more sensitive to statistical regularities in sequences performed by a human agent versus self-propelled ‘ghost’ events. Secondly, we investigated whether regularities are learned better when they are associated with contingent effects. Both implicit and explicit measures of learning were compared between agent and ghost conditions. Implicit learning was measured via predictive eye movements to upcoming actions or events, and explicit learning was measured via both uninstructed reproduction of the action sequences and verbal reports of the regularities. The findings revealed that participants, regardless of condition, readily learned the regularities and made correct predictive eye movements to upcoming events during online observation. However, different patterns of explicit-learning outcomes emerged following observation: Participants were most likely to re-create the sequence regularities and to verbally report them when they had observed an actor create a contingent effect. These results suggest that the shift from implicit predictions to explicit knowledge of what has been learned is facilitated when observers perceive another agent’s actions and when these actions cause effects. These findings are discussed with respect to the potential role of the motor system in modulating how statistical regularities are learned and used to modify behavior.

Keywords Action prediction · Action sequences · Statistical learning · Implicit and explicit learning · Eyetracking

Introduction

Predicting the behavior of other people is central to social cognition and interaction. As we observe others, we automatically predict the unfolding movements and future course of their actions (Flanagan & Johansson, 2003). In everyday life, many of the actions we observe are embedded within continuous

temporal sequences. Imagine the act of baking a cake: This action consists of a continuous stream of individual action steps, such as gathering ingredients, measuring them into bowls, mixing things together, pouring the batter into a tin, and so forth. The ability to anticipate the upcoming events in a sequence is an indicator that the observer possesses some knowledge of the overarching structure of the global action and the relations between the individual steps. Perceiving the boundaries of the distinct elements in a sequence and anticipating what follows is crucial in order for our cognitive system to perceive the overarching activity as coherent and meaningful (Zacks & Tversky, 2001). In the present study, we investigated whether statistical regularities in novel, unfamiliar sequences support the ability to generate predictions of future events during observation.¹ Specifically, we investigated whether

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¹ Unlike the cake example above, the sequences used in the present study were abstract, in the sense that they did not lead to a global action goal. This was done to ensure that predictions could only be based on acquiring knowledge of the sequence regularities, rather than on prior knowledge about the overarching event structure.

observers make anticipatory gaze fixations to upcoming action events on the basis of their transitional probabilities alone, and whether observers re-create learned regularities in their own action performance following observation.

Statistical learning in the domain of action

Statistical learning (SL) refers to the ability to detect regularities from structured input and operates across sensory domains (Conway & Christiansen, 2005; Krogh, Vlach, & Johnson, 2013). From early in life, humans are sensitive to multiple sources of statistical information in visual and auditory stimuli (Saffran, Johnson, Aslin, & Newport, 1999). Converging evidence indicates that SL skills are rapid and automatic, often occurring without the learner being consciously aware that he or she has learned anything at all (Turk-Browne, Scholl, Chun, & Johnson, 2008). This has led to the assumption that SL is a domain-general mechanism, with similar underlying computations and outcomes across sensory modalities. However, there is also evidence that the outcomes of SL are specific to the modality in which the stimuli are learned. For instance, one study (Conway & Christiansen, 2006) presented participants with auditory, tactile, and visual sequences defined by respective artificial grammars. The findings showed that sensitivity to statistical features was specific to each sensory modality, suggesting that SL involves “distributed, modality-constrained subsystems” (Conway & Christiansen, 2006, p. 911).

Does sensitivity to statistical regularities extend to the domain of action? If so, does SL operate in a domain-general manner across all forms of perceptual events, or are there specialized subsystems that facilitate SL particularly for observed *actions*? An initial study on action sequence processing by Baldwin, Andersson, Saffran, and Meyer (2008) demonstrated that observers can rely on statistical regularities to segment action streams into discrete steps, even when transitional probabilities are the only information available for identifying action segments. At a group level, participants’ performance on this action segmentation task was comparable to performance on similar tasks in the language domain. Developmental research has demonstrated similar findings with preverbal infants (Roseberry, Richie, Hirsh-Pasek, Golinkoff, & Shipley, 2011; Saylor, Baldwin, Baird, & LaBounty, 2007; Stahl, Romberg, Roseberry, Golinkoff, & Hirsh-Pasek, 2014), showing that these segmentation skills emerge early in development. Similarity in performance across studies has led researchers to speculate that a common “statistical tracking mechanism” (Baldwin et al., 2008, p. 1404) is shared between the processing of action and the processing of other forms of perceptual stimuli.

Segmentation reveals whether observers have sensitivity to the sequence structure after learning has occurred. Typical paradigms measure segmentation by the ability to remember the items that were observed during a previous

learning phase (e.g., Baldwin et al., 2008; Saffran, Newport, Aslin, Tunick, & Barrueco, 1997). However, current theories of action perception claim that continual, automatic prediction of upcoming actions is a central feature of action processing (Kilner, Friston, & Frith, 2007a, 2007b). Importantly, predicting the outcomes of ongoing actions requires integrating prior knowledge about the most likely outcomes of the action with incoming perceptual input. Though active motor experiences are one important source of action knowledge (Calvo-Merino, Grèzes, Glaser, Passingham, & Haggard, 2006; Libertus & Needham, 2010; Sommerville, Woodward, & Needham, 2005), motor experience alone is insufficient to explain the full range of infant and adult capabilities for learning about actions (Hunnius & Bekkering, 2014). Statistical-learning skills are therefore a candidate mechanism for how humans learn and generate predictions about upcoming action steps when observing novel, unfamiliar sequences (Ahlheim, Stadler, & Schubotz, 2014), though direct evidence for this mechanism does not yet exist. As we discuss below, we hypothesized that observing human action engages specialized cognitive processes that particularly facilitate the learning of observed action sequences relative to visual event sequences.

Outcomes of learning: Implicit and explicit measures

The outcomes of SL have long been a topic of debate; in particular, discussions have focused on whether and under what conditions SL results in explicit or implicit learning outcomes (Perruchet & Pacton, 2006). Typical findings have shown that SL usually occurs automatically and without conscious intent; people are often unaware of the regularities they have learned (e.g., Haider, Eberhardt, Esser, & Rose, 2014; Turk-Browne, Jungé, & Scholl, 2005; Turk-Browne et al., 2008). The behavioral indicators of implicit learning are typically faster reaction times (Fiser & Aslin, 2002) or anticipatory eye movements (Marcus, Karatekin, & Markiewicz, 2006), and participants are usually unaware of the subtle changes in their own behavior as a result of learning. On the other hand, SL can also result in explicit knowledge about what was learned (Bertels, Franco, & Destrebecqz, 2012; Esser & Haider, 2017b). Explicit learning is typically measured by recognition or recall, which requires “conscious, or deliberate, access to memory for previous experiences” (Gomez, 1997, p. 166). In the present study, we assessed multiple measures of learning to explore how the learned information is transferred into behavior. If participants learned the statistical regularities, they could in principle predict what would occur next and shift their gaze to the next event in the sequence. If implicit knowledge from observation can be accessed and used to modify behavior, participants might also reproduce the observed regularities and report knowledge about the sequence structure.

The role of the motor system during action observation

Observing actions engages neural networks that differ from those involved in general visual and attention processes (Adams, Shipp, & Friston, 2013; Ahlheim et al., 2014; Schubotz & von Cramon, 2009). For instance, neuroimaging research has revealed the existence of a network of sensorimotor brain regions, collectively termed the “action-observation network” (AON), that are specifically engaged when observing another person’s actions (Gallese & Goldman, 1998; Kilner, 2011). Activity in the AON, also sometimes termed “motor resonance” (Rizzolatti & Craighero, 2004) or “simulation” (Blakemore & Decety, 2001), is thought to facilitate the prediction of observed actions by simulating how one would perform the action oneself. Predictive accounts of the motor system propose that we employ our own motor system using an internal, feed-forward model to predict the behavior of other people we observe (e.g., Kilner et al., 2007a).

In the context of embodied accounts of action observation, the motor system facilitates efficient transformation of visual information into action knowledge in the observer’s motor system. Supporting evidence from a separate line of research on observational learning has shown that observers are consistently better at imitating and learning novel tool functions when observing a human actor relative to any other form of visual observation (for a review, see Hopper, 2010). These behavioral studies employed a so-called “ghost display,” a method in which objects appear to move on their own with no agent intervention. In the present study, we adopted the ghost-display method in order to test the hypothesis that the learning advantage when observing another human, relative to a nonagent ghost display, extends to action predictions based on statistical learning.

The role of effects in continuous action sequences

Goal-directed actions typically result in perceivable effects, such as the sound of a whistle as it is blown. Through repeated observation, these effects become linked to the actions that consistently precede them and create “bidirectional action–effect associations” (Elsner & Hommel, 2001). Prior research has suggested that it is the effects of actions themselves that people anticipate when planning their own movements (Hommel, 1996). In the field of implicit-learning research, action effects have been shown to enhance implicit sequence learning when participants’ own motor responses result in predictable action effects (e.g., Haider et al., 2014). Recent work has suggested that action effects may also be particularly important for transferring learning from implicit into explicit awareness (Esser & Haider, 2017a, 2017b). These findings demonstrate that action–effect associations likely play a

central role in establishing the contextual knowledge needed for making action predictions. Though much of this work has investigated action effects in sequence learning of motor responses (e.g., using the standard *serial reaction time task*), there is also evidence to suggest that action effects guide our predictions during observation alone (Paulus, van Dam, Hunnius, Lindemann, & Bekkering, 2011).

How do sensory effects influence *observers’* sensitivity to statistical regularities when they are embedded within continuous sequences, as is the case during daily real-life perception? On the basis of ideomotor theory (James, 1890) and the related action-effect principle (Hommel, 1996), observers should be better at learning action contingencies when these contingencies are paired with an effect, even when they do not produce the effects themselves. A matter that has not received much attention, however, is the fact that nonaction visual events also result in sensory effects, such as a crashing wave. So far, we have defined such effects as *action* effects to be consistent with prior research, but it is possible that sensory effects lead to similar bidirectional associations in any form of perceptual sequence. In fact, another theory (Schubotz, 2007) has suggested that the prediction of sensory effects occurs within our sensorimotor system and can be generalized to any form of perceptual event, whether action or not. On the other hand, as we described above, evidence for enhanced learning from observing action suggests that action effects should be perceived and learned qualitatively differently than the effects of nonaction perceptual events. In the present study, we manipulated whether statistical regularities were paired with an action effect in order to investigate the importance of observed effects for action predictions.

The present experiment

The central focus of this study was to investigate whether observers spontaneously exploit statistical information in continuous action sequences in order to predict upcoming actions. Our experiment included two manipulations targeting two primary components of action processing: (a) the role of observing an actors versus a ghost display (Agent and Ghost conditions; between subjects) and (b) the influence of action effects versus the lack of effects (effect and no-effect pairs; within subjects). These conditions were assessed using an anticipatory fixation eyetracking paradigm during action observation, which has been established as a measure of visual predictions (Hunnius & Bekkering, 2010). In addition, we examined the link between predictive looking during observation and the subsequent action production. For this third aim, postobservation action performance and verbal reports were analyzed as complementary measures of implicit and explicit learning, respectively.

Method

Participants

Fifty university students participated in this study (25 in each condition [Agent and Ghost]; 43 females, seven males; $M = 20.07$ years, range = 18–25 years, $SD = 2.29$). Participants were recruited via an online system for students at the university and were awarded course credit for participation. Seven participants were excluded from the analyses for not meeting the inclusion requirements for total looking time (see the Data Analysis section), resulting in 43 participants in the final sample (23 in the agent condition and 20 in the ghost condition).

Stimuli

Participants’ eye movements were recorded with a Tobii T60 eyetracker (Tobii, Stockholm, Sweden) with a 17-in. monitor. Participants sat approximately 60 cm away from the screen. Stimuli were presented with the Tobii ClearView AVI presentation software, and sounds were played through external speakers.

Participants observed a full-screen ($1,280 \times 1,024$ pixels) film of a sequence involving a multi-object device that afforded six unique manipulations and a central, star-shaped light (Fig. 1). To avoid confusion, we will subsequently refer to the individual object manipulations in the sequence as “events”, as in one condition they were human actions and

in the other they were object movements. The movies were filmed with a Sony HandyCam video camera and edited using Adobe Premiere Pro Cs5 software. The same device used during filming was presented to participants before and after the observation phase.

Sequence We constructed four pseudo-randomized sequences, using the program *Mix* (van Casteren & Davis, 2006). All sequences contained two deterministic pairs (transitional probability between events = 1.0), labeled “effect” and “no-effect” pairs (described in more detail in the following paragraph). The second event of each deterministic pair was labeled a “target,” since these were the events that became predictable as the sequence unfolded. All other possible random pairs occurred with equal frequency (transitional probabilities between events = .167; Fig. 1B). No event or pair could occur more than three times consecutively. All pairs and random events occurred 12 times (targets thus occurred 12 times within pairs and 12 times outside of pairs). In total, participants viewed 24 deterministic pairs (12 effect and 12 no-effect pairs) and 48 random unpaired events, for sequences of 96 total actions or events. The effect and no-effect pairs were composed of two actions that were randomly selected from the six possible actions. Two sets of the four sequences were created: the two actions composing the effect pair in one set became the no-effect pair in the second set, and vice versa. Thus, there were eight possible sequences within each condition and 16 videos in total; participants were randomly assigned to view one of these videos.

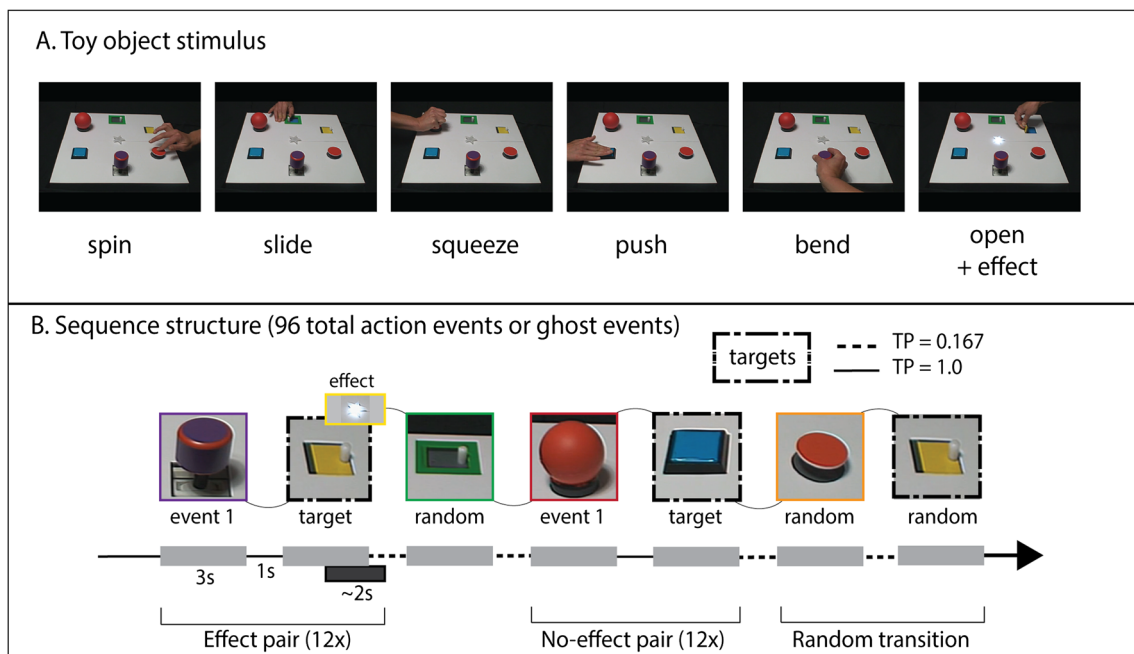


Fig. 1 Overview of the experimental design. **a** Example frames from the video stimuli of the agent condition. **b** Schematic illustrating the deterministic pairs and transitional probabilities within sequences during the observation phase

The ‘effect pair’ caused a central star to light up, whereas the ‘no-effect pair’ caused no additional effect. We will subsequently refer to the second events of both pairs as *targets*, since these were the events that became predictable as the sequence unfolded. The effect onset occurred at a natural midpoint of the target event during the effect pair: For example, during the target *open*, the light turned on the moment the yellow door was fully open, and turned off again after it closed (see Fig. 1A).

Targets could also occur elsewhere in the sequence outside of the deterministic pair (see Fig. 1B). In these instances, the effect never occurred. This ensured that the second event did not independently predict the effect, so observers were required to learn the two-step pair structure in order to accurately predict the effect.

Each video sequence was divided into four blocks, with the viewing angle oriented from a different side of the box for each block. This was done to dissociate the events (and their corresponding objects) with their spatial location, and thus to ensure that the observer could not predict the next event on the basis of its location on the screen. Each block lasted approximately 90 seconds and consisted of 24 events. Brief cartoon animations were presented between blocks in order to reengage the participant’s attention. At the beginning of a block, one 4-s still frame of the stimulus was presented in order to allow observers to reorient to the new perspective. Movies were approximately 7 min long. Engaging, upbeat music was played throughout the entire demonstration that did not correspond in any way to the unfolding sequence.

Agent condition In the agent condition movies, a hand manipulated the stimulus objects in a continuous sequence. For each

action, the hand entered the screen closest to the object on which it acted. Each action was exactly 3 s in duration, with a 1-s pause between actions during which the hand was off-screen and only the stimulus was visible.

Ghost condition In the ghost condition, the objects appeared to move on their own, with a spotlight focused on the current event (see Fig. 2). The spotlight gradually illuminated each object just prior to its movement onset and faded again after the object had ceased moving. Between ghost events there was a 1-s pause during which it was ambiguous where the spotlight would next begin to appear, which matched the period of time that the actor’s hand was off-screen in the agent condition. Like the actor’s hand, the spotlight cued which object would subsequently move. The intensity and focus of the spotlight were equal for all objects. The sequence order and timing of events were otherwise identical to the videos in the agent condition.

Procedure

Participants were first seated at a table upon which the stimulus device was placed. The side facing each participant was counterbalanced. Participants were told they would watch a video of a person interacting with the device and were allowed to first familiarize themselves with the objects before beginning the experiment. The side of the object facing the participant during the action execution phase was kept the same as during the initial familiarization. After familiarization, participants moved to a chair positioned in front of the eyetracking monitor for the observation phase in which they observed the stimuli videos. First, the eyetracker was calibrated using a standard 9-point calibration sequence provided by Tobii Studio software.

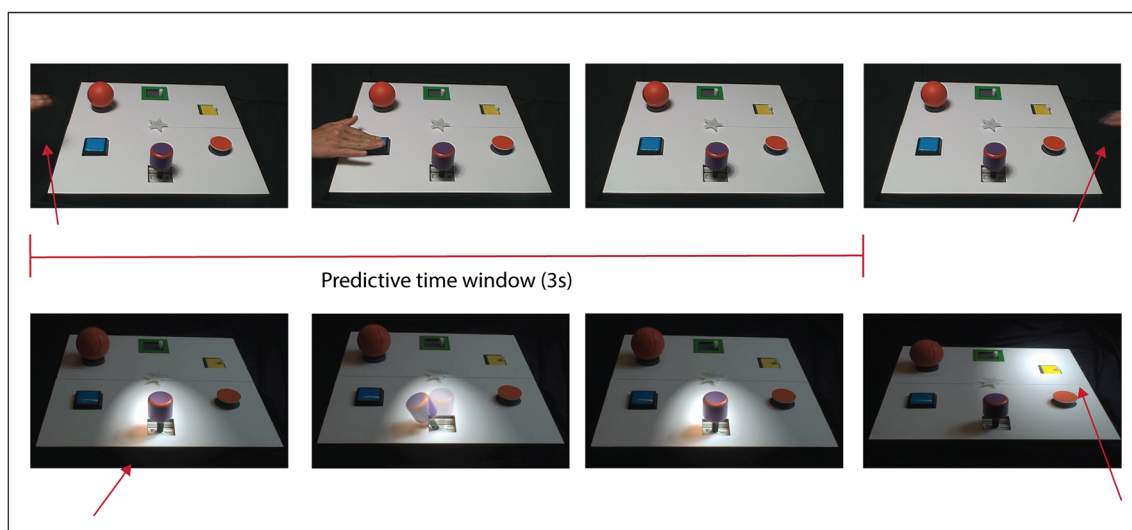


Fig. 2 Predictive time windows in the Agent and Ghost conditions: Example frames illustrating the predictive time windows in both conditions. Arrows indicate the first frame in which the agent’s hand

appears (agent condition) and in which the spotlight focuses on the target object (ghost condition)

Calibration was repeated until valid calibration data was acquired for at least eight calibration points. Following calibration, participants were shown one of the eight stimulus sequences. They were told that they would be shown a video but were not given specific viewing instructions.

Immediately after the observation phase, participants returned to the table and were told that they could freely interact with the stimulus for 1 min (this duration was based on pilot testing). Participants were given no instruction, as our aim was to investigate whether they would spontaneously integrate observed regularities into their own actions in the absence of any task demand. The experimenter sat opposite the participant and monitored their behavior, pressing a hidden button that activated the effect (i.e., central star light) whenever he or she performed the Effect pair. After 1 min, the experimenter ended the action execution phase and then asked each participant the following questions: “Do you know how to make the light turn on?” and “Did you notice any other pattern in the movies?” If participants responded “yes” they were then asked to demonstrate the correct sequence on the device. A camera facing the participant recorded this session and behavior was later coded offline to assess action performance. Each participant completed one action sequence.

Data analysis

Eyetracking data

Participants with total fixation time more than one standard deviation below the mean were excluded due to relative inattention to the movies. These participants yielded gaze data for less than 25% of the demonstration, which corresponded to only three observations of each pair and was insufficient to assess learning over the course of the experiment. This resulted in the exclusion of two participants in the agent condition and five participants in the ghost condition (see the Participants section above).

The eye movement data were exported from Tobii ClearView analysis software and separated into discrete fixations using a customized software program with a spatial filter of 30 pixels and a temporal filter of 100 ms. Fixation data was imported into Matlab for further analysis. Regions of interest (ROI) of identical size were defined around each object (250 × 250 square pixels), and a smaller ROI (130 × 130 square pixels) was defined around the light (due to its smaller size relative to the objects).

For the agent condition, fixations were considered predictive if they occurred in the time window from when the actor’s hand entered the screen to perform the first action of a pair until the frame before the hand reappeared for the target action (Fig. 2). This corresponds to the time at which the participant had enough information to predict the next action before its

onset. For the ghost condition, this time window was defined from the moment the spotlight highlighted the first object until the frame before the light shifted toward the second object of a pair. The time windows were identical in length in both conditions. Because the main aim of this study was to examine prediction, only predictive gaze fixations were included in our analyses (i.e., we did not examine reactive fixations).

To assess predictive gazes during observation, we compared the proportions of fixations to correct versus incorrect objects (Implicit Learning Measure I). Implicit Learning Measure I reflects the extent to which observers predicted the correct location of an upcoming event, relative to other locations. Second, we analyzed the proportions of correct predictive fixations over the course of the experiment to examine how learning unfolded over time. Third, the proportions of predictive fixations to target objects were compared between deterministic and random transitions (Implicit Learning Measure II). Learning Measure II reflects the frequency of predictive looks to the target actions during predictable relative to unpredictable trials. We describe both measures in more detail below (Fig. 3).

Implicit learning measure I: Correct versus incorrect locations

Target regions were defined around the location of the second events of each pair. Fixations to targets during the predictive time windows were counted as *Correct*, and fixations to the four remaining objects as *Incorrect*. Objects currently being manipulated (i.e., the first action of the pair) were excluded from the analyses. The first trial of each pair was not analyzed, because participants were not expected to correctly predict the first observation of a pair. If participants learned the pair structure, we expected them to make more fixations to the locations of target objects than to any other object during the predictive time windows. For both effect and no-effect pairs, we calculated the proportions of correct and incorrect fixations out of the total fixations to all objects (Eqs. 1 and 2). Because there were uneven numbers of correct and incorrect locations, the incorrect proportion was defined as the average number of fixations to the four remaining objects out of the total number of fixations. This location measure represents observers’ bias for looking toward the correct target, relative to other objects, before it was acted upon. For additional analyses in which we include fixations to the action effect, see the [supplementary materials](#).

$$Correct_{target} = \frac{\#fixations\ to\ target}{total\ \#fixations\ to\ objects} \quad (1)$$

$$Incorrect_{target} = \frac{\#fixations\ to\ other\ 4\ objects/4}{total\ \#fixations\ to\ objects} \quad (2)$$

Implicit learning measure II: Deterministic versus random transitions Our second learning measure compared fixations to targets during deterministic versus random trials (Eqs. 3 and

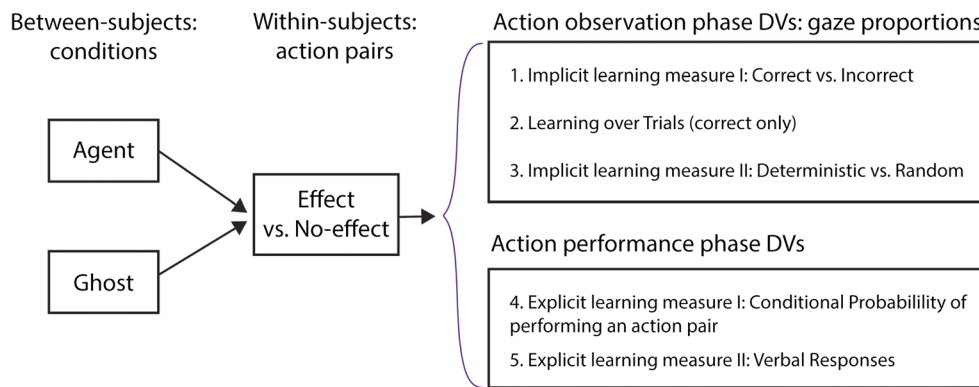


Fig. 3 Overview of the experimental design and dependent variables

4). Random trials were defined as transitions between any possible event and the subsequent occurrence of a target event outside of a deterministic pair. We discarded all repetition trials (e.g., *push* followed by *push*) because it was impossible to determine whether fixations during these trials were predictive or reactive (i.e., simply not moving the eyes). This analysis thus enabled us to compare fixations to the same location (target objects) in different statistical contexts².

$$\text{Deterministic} = \frac{\# \text{fixations to target (predictive trials)}}{\text{total} \# \text{fixations to objects}} \quad (3)$$

$$\text{Random} = \frac{\# \text{fixations to target (nonpredictive trials)}}{\text{total} \# \text{fixations to objects}} \quad (4)$$

Behavioral data

Explicit learning measure I: Action performance Participants' self-produced action sequences were coded from the videotape recordings. Each object manipulation was counted as a single action. We calculated the conditional probability of performing the second action of a pair (*B*), given performance of the first action (*A*), to account for variation in the overall length of participants' sequences. Conditional probability was defined as:

$$P(B|A) = \frac{P(A, B)}{P(A)} \quad (5)$$

Explicit learning measure II: Verbal responses Responses to the experimenters' explicit questions—"Do you know how to make the light turn on?" and "Did you notice any other pattern in the movies?"—were coded as "yes" or "no"; if a response was "yes," it was further coded as "yes"-correct or "yes"-incorrect, depending on whether or not the participant had demonstrated the correct sequence on the first attempt.

Proportions of participants who indicated each response type were calculated for each pair, per condition.

Results

Eye movement data

To examine whether the Agent and Ghost displays elicited similar rates of overall visual attention to the objects of interest, we compared the numbers of predictive fixations between the two conditions. There were no differences in the numbers of anticipatory fixations made during target trials (Ghost = 41.55, *SEM* = 4.80; Agent: *M* = 44.61, *SEM* = 3.41; *p* = .60) or in the total numbers of fixations made across the entire demonstration (*p* = .21), suggesting that differences between the visual stimuli in the Agent and Ghost conditions did not underlie any potential differences in anticipatory fixations. Analyses of the total looking times, in seconds, are reported in the [supplementary materials](#).

Implicit learning measure I: Correct versus incorrect locations

Our primary learning measures in each condition are presented in Table 1. Proportions of gaze fixations were analyzed via a repeated measures analysis of variance (ANOVA), with Prediction (Correct vs. Incorrect) and Pair (Effect vs. No effect) as within-subjects factors and Condition (Agent vs. Ghost) as a between-subjects factor. This analysis revealed a main effect of Prediction, indicating that participants made a higher proportion of correct relative to incorrect predictive fixations across pairs (mean difference = .14 [*SEM* = .04]), $F(1, 40) = 16.27, p < .001, \eta_p^2 = .29$. There were no other significant main effects or interactions (*ps* > .13). The results of additional analyses that include the location of the action effect as a correct location are available in the [supplemental information](#).

Learning over trials To examine changes in predictions across trials, we performed a general estimating equations (GEE) analysis. GEE analyses are a preferred method for analyzing

² Note that this equation is identical to Eq. 1.

Table 1 Main implicit and explicit dependent measures, separated by condition

Learning Measure	Pair		Agent (<i>N</i> = 23)		Ghost (<i>N</i> = 20)	
			Mean	<i>SD</i>	Mean	<i>SD</i>
I: Correct vs. Incorrect	Effect	Correct (Eq. 1)	.39	.26	.34	.33
		Incorrect (Eq. 2)	.09	.05	.11	.07
	No-effect	Correct (Eq. 1)	.26	.28	.25	.22
		Incorrect (Eq. 2)	.19	.07	.19	.06
II: Deterministic vs. Random	Effect	Deterministic (Eq. 3)	.39	.26	.34	.33
		Random (Eq. 4)	.25	.20	.18	.16
	No-effect	Deterministic (Eq. 3)	.26	.28	.25	.22
		Random (Eq. 4)	.13	.14	.14	.12
Action Performance	Effect	Conditional probability (Eq. 5)	.54	.36	.30	.30
	No-effect		.29	.36	.09	.16
Verbal Response (“yes” – correct)	Effect	% participants	68.4%		15.4%	
	No-effect		5.9%		7.7%	

For Learning Measure I, column 3 refers to proportions of correct and incorrect fixations. For Learning Measure II, column 3 refers to proportions of correct fixations on deterministic or random trials.

data with repeated measures that contain missing points, such as trials in which no anticipatory fixations were recorded, because they do not apply list-wise exclusion of cases (Zeger, Liang, & Albert, 1988). Proportions of correct fixations to the targets were entered as the dependent variable in a linear, model-based GEE with an unstructured working correlation matrix. Condition (between-subjects), Trial (within-subjects), and Pair (within-subjects) were entered as the predictors in a factorial model. In this analysis, the first trial was included (in contrast to the analyses for Learning Measures I and II).

The GEE analysis yielded significant main effects of Trial [$\chi^2(11) = 47.19, p < .001$] and Pair [$\chi^2(2) = 26.89, p < .001$], a significant interaction between Condition and Trial [$\chi^2(11) = 21.52, p = .028$], a significant interaction between Condition and Pair [$\chi^2(2) = 8.70, p = .003$], and a three-way Condition \times Trial \times Pair interaction [$\chi^2(11) = 22.96, p = .02$]. The Condition \times Pair interaction revealed that proportions of correct fixations were significantly greater in the Agent than in the Ghost condition for the Effect pair (mean difference = .18 [$SEM = .05$], $p < .001$), but not for the No-effect pair (mean difference = $-.09$ [$SEM = .06$], $p = .11$).³ As is illustrated in Fig. 4, the Condition \times Trial interaction revealed that the Agent and Ghost conditions did not differ from one another on the very first ($p = .45$) or second ($p = .15$) trial. By the third trial, the participants in the Agent condition made more correct fixations than did those in the Ghost condition (mean difference = .28 [$SEM = .12$], $p = .015$), and this pattern continued for several trials. The two conditions converged again by the 6th trial ($p = .53$) for the remainder of the experiment.

³ Note that the interaction between condition and pair was not statistically significant in our first analysis. This is likely due to the fact that the first analysis included both correct and incorrect fixations, whereas the learning-over-trials analysis examined correct fixations only.

Together, these findings suggest that participants showed a selective learning benefit for making correct anticipations when viewing an agent producing action effects, relative to the other observation contexts.

Implicit learning measure II: Deterministic versus Random transitions The proportions of gaze fixations to target objects (Eqs. 3 and 4) were entered as the dependent variables into an ANOVA, with Transition (Deterministic vs. Random) and Pair (Effect vs. No-effect) as within-subjects factors and Condition (Agent vs. Ghost) as a between-subjects factor. This revealed a main effect of Transition, showing that participants made more target fixations during Deterministic than during Random transitions, across conditions and pairs, $F(1, 42) = 42.9, p < .001, \eta_p^2 = .51$. No other effects or interactions emerged ($ps > .11$).

Explicit measures of learning

Explicit learning measure I: Action performance Across conditions, participants performed sequences with an average length of 26.22 actions ($SD = 7.1$) and performed a mean of 2.12 Effect pairs and 0.64 No-effect pairs (see Table 1 for additional descriptive measures). There were no differences in the total lengths of the action sequences performed between conditions ($p = .19$).

Conditional probabilities for performing the target action given the performance of the first action of the pair were entered in an ANOVA, with Pair (Effect vs. No-effect) as a within-subjects factor and Condition (Agent vs. Ghost) as a between-subjects factor. This revealed main effects of Condition and Pair: The participants in the Agent condition were more likely to perform an action pair than were those in the Ghost condition, $F(1, 34) = 11.57, p = .002, \eta_p^2 = .25$ (see

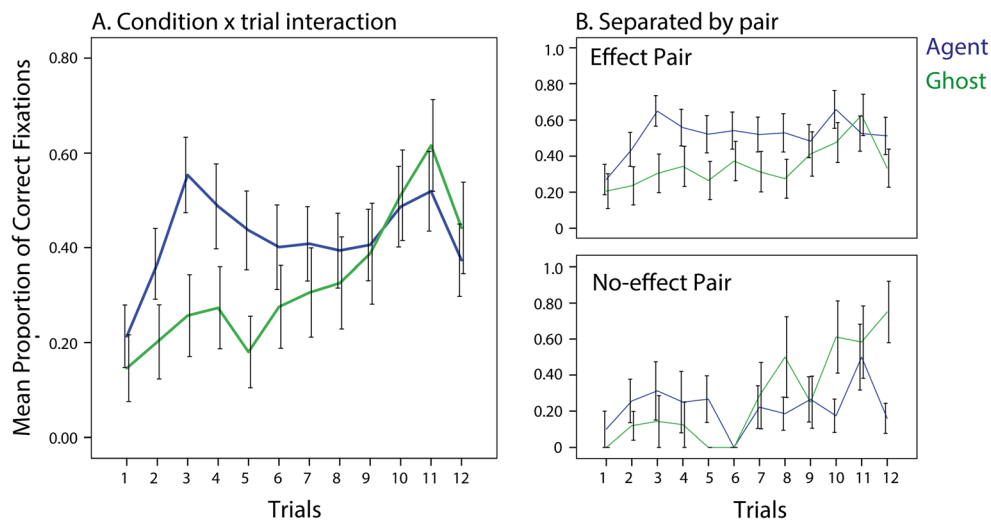


Fig. 4 Learning over time. Estimated marginal means of correct predictive fixations across pairs as a function of trial, (left) collapsed across pairs and (right) separated by Effect and No-effect pairs. Bars represent standard errors

Fig. 5a). Across conditions, participants were more likely to perform the Effect pair than the No-effect pair, $F(1, 34) = 8.25$, $p = .007$, $\eta_p^2 = .20$. We found no interaction between pair and condition ($p = .78$).

To assess whether the participants in each group performed more pairs than would be expected on the basis of chance, we conducted a one-sample t test to compare the mean conditional probabilities of performing each pair against a chance level of .167 (one out of six possible actions, given any previous action). This revealed that the participants in the Agent condition performed Effect pairs significantly more than we would expect from chance ($p < .001$), whereas the participants in the Ghost condition did not ($p = .13$). In neither condition were the No-effect pairs performed at an above-chance level ($ps > .05$).

To investigate whether action execution was related to anticipatory looking behavior, we correlated the proportions of correct target fixations (Eq. 1) and the conditional probabilities of producing action pairs for each pair type. Across conditions, there was a significant positive correlation between target fixations during Effect pairs and the conditional probability of producing Effect pairs, $r(35) = .41$, $p = .02$, indicating that participants who demonstrated higher rates of learning during the observation phase were more likely to reenact the action effect during the subsequent behavioral session (Fig. 5b). There was no correlation for the No-effect pair, $r(36) = .01$, $p = .97$. These correlation coefficients differed significantly from one another, $Z = 1.75$, $p = .04$.⁴

⁴ For thoroughness, we also averaged across pairs and correlated the fixation proportions with conditional probabilities for the Agent and Ghost conditions separately. Across pairs, there were no significant correlations for either group, $ps > .42$. These correlation coefficients did not differ significantly from one another ($Z = .41$, $p = .34$).

Explicit learning measure II: Verbal responses Figure 5c illustrates the distributions of participants per each explicit response type to the experimenter's questions following the action execution phase, separated by pair and condition. The pie charts reflect the following pattern: 94.7% of participants in the agent condition reported explicit knowledge of the Effect pair; of these, 72.2% were correct and 27.8% were incorrect. Only 53.8% reported explicit knowledge of the pair in the Ghost condition; 28.6% of these were correct and 71.4% were incorrect. Furthermore, only 40% reported knowledge of the No-effect pair across conditions, and those who did were usually incorrect (93.3% of these 40%).

To compare these proportions of participants (Agent vs. Ghost) to one another, we calculated the confidence intervals of the difference between them (the difference between proportions is statistically significant whenever the confidence interval excludes zero; Newcombe, 1998; Wilson, 1927). Table 2 reports the confidence intervals for the differences in proportions for each response type. For the Effect pair, the proportion of participants who responded “yes” and were correct was significantly greater in the Agent than in the Ghost condition. A higher proportion of participants reported knowledge of the Effect pair—and could demonstrate the correct sequence—in the Agent condition than in the Ghost condition. Likewise, significantly more participants reported *no* knowledge of the Effect pair in the Ghost condition than in the Agent condition. For the No-effect pair, the pattern of responses was similar across conditions. Thus, participants observing an actor were more likely to retain precise knowledge that they could verbalize about the pair structure, but only when the actor's actions led to a causal effect. Participants observing ghost events were less likely to report verbal knowledge, and when they did, their representations of the pair structure were more likely to be inaccurate.

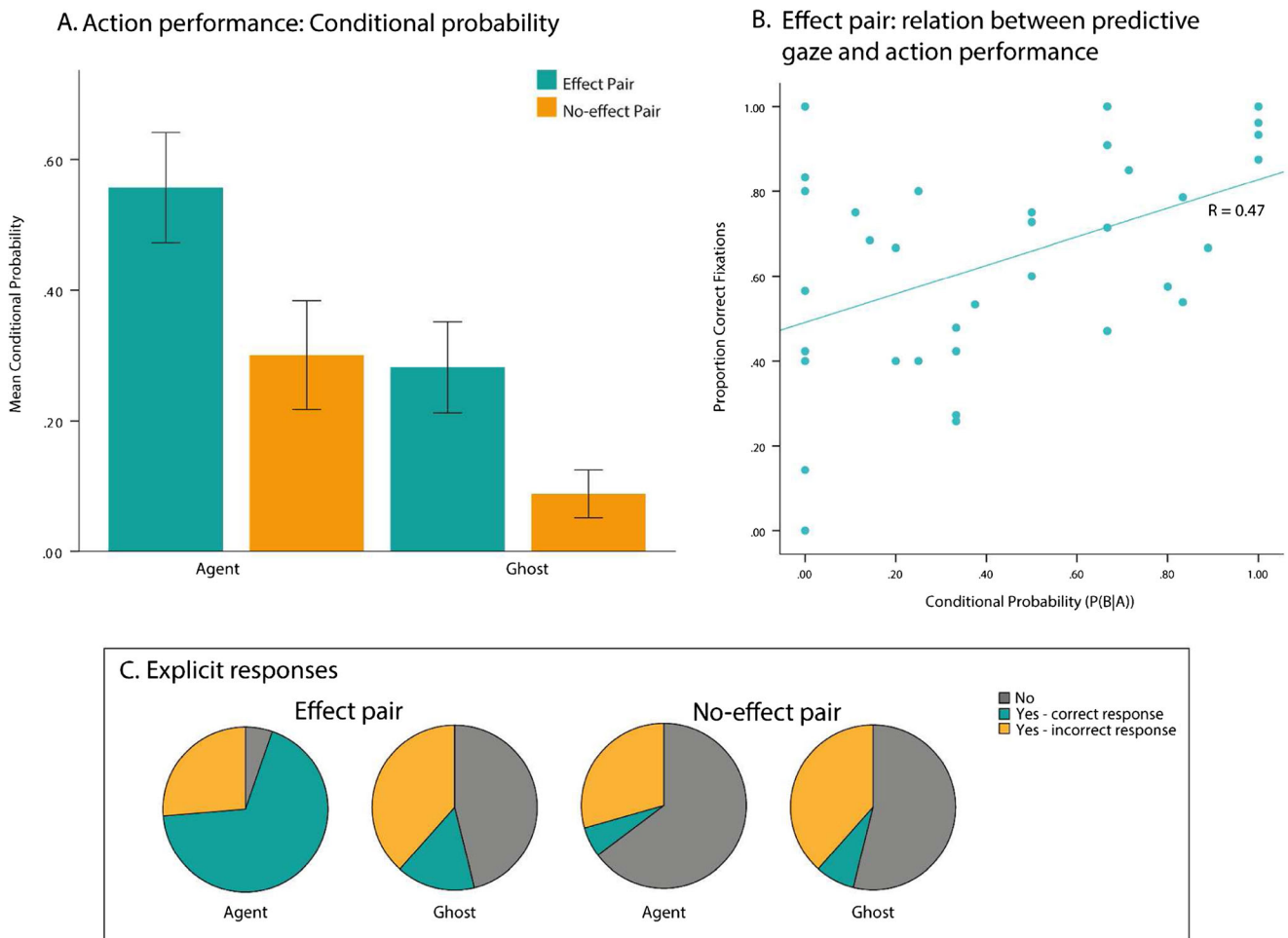


Fig. 5 Action performance and verbal awareness. (A) Mean probabilities of performing Effect and No-effect pairs $[P(B|A)]$. Bars represent standard errors. (B) Scatterplot illustrating the relation between predictive fixations (Eq. 1) and action performance (Eq. 5) for effect pairs, across conditions.

(C) Pie graphs showing the percentages of participants who gave each response type to the experimenter’s question. For the Effect pair, this question was “Do you know how the light turns on?,” and for the No-effect pair it was “Did you see any other pattern in the movies?”

Discussion

In the present study we investigated whether observers can learn statistical regularities during the observation of continuous action or event sequences. Specifically, we measured anticipatory gaze fixations as an implicit measure of whether

participants could use statistical information to predict upcoming actions or events in the sequence. After learning, we measured spontaneous action performance and verbal reports as explicit measures of whether observed statistical regularities influenced participants’ self-produced actions and knowledge of the sequence.

Table 2 Mean differences (and confidence intervals) between conditions (agent – ghost) in the proportions of participants reporting each response type for effect and no-effect pairs

Response	Effect Pair		No-Effect Pair	
	Diff($P_a - P_b$)	95% CI	Diff($P_a - P_b$)	95% CI
“No”	-.41	[.11, .66]*	.11	[-.22, .41]
“Yes”-correct	.53	[.18, .73]*	-.02	[-.20, .28]
“Yes”-incorrect	-.12	[-.18, .42]	-.09	[-.22, .40]

Diff($P_a - P_b$) indicates the difference between the proportions of participants in the Agent and Ghost conditions. * Statistically significant difference between the two sample proportions ($p < .05$).

Implicit learning: Predictive gaze

Across conditions and pairs, participants demonstrated a robust tendency to predict correct relative to incorrect locations. They also predicted the target more frequently during deterministic relative to random transitions between events. In other words, they looked to where a target event was statistically likely to occur next, and they looked to the targets selectively when they were likely relative to when they were unlikely to occur next.

When examining correct predictions over time, an interaction effect between these two manipulations emerged:

Participants appeared to learn the regularities best when they observed an actor produce an action effect. In addition, different patterns emerged between the Agent and Ghost conditions for implicit- and explicit-learning outcomes, as measured by visual anticipations, action performance, and verbal knowledge of the pair structure. Specifically, observing actions in the agent condition did not seem to uniquely benefit predictive gaze performance relative to observing visual events in the ghost condition; however, it did increase reproduction of the action pair and verbal knowledge about the pair structure. Importantly, these differences were apparent only for the sequence pair that resulted in an action effect. One explanation for these patterns is that action-specific processing in the agent condition facilitated the transfer from implicit (i.e., eye movements) to explicit (i.e., self-produced actions, verbal awareness) knowledge, as we discuss in the following sections.

Actions versus perceptual sequences

Participants demonstrated learning when observing both an actor and a ghost event, as indicated by their correct predictive looks while observing the sequences in both conditions. This finding suggests that statistical learning operates consistently across the different types of perceptual events, both action and nonaction. Interestingly, learning emerged earlier in the agent than in the ghost condition. Consistent with prior research, this finding reveals a subtle learning benefit when observing an agent relative to other forms of visual displays (Hopper, Flynn, Wood, & Whiten, 2010; Hopper, Lambeth, Schapiro, & Whiten, 2015). According to motor-based accounts of action observation, this benefit originates from internal predictive models based in the motor system (Kilner et al., 2007b; Stapel, Hunnius, Meyer, & Bekkering, 2016). Here we showed that observers demonstrate faster learning in the agent than in the event condition. Specifically, participants' rates of correct fixations to target actions increased more quickly in the agent condition, revealing that participants more easily detected the statistical relations between the actions and could modify their looking behavior accordingly. Interpreted within these motor-based accounts, this result may reflect a more efficient ability to transfer knowledge acquired from visual statistical learning into action predictions that are generated in the motor system (Kilner, 2011).

As we discussed in the introduction, developmental studies have shown that children learn significantly better from observing an agent performing actions than from other forms of observational learning (Hopper et al., 2010). One recent study, in fact, showed that toddlers were able to learn action sequences when observing an actor, but not when observing a ghost event (Monroy, Gerson, & Hunnius, 2017). This finding may reflect an interesting developmental shift, in which actions provide a unique context that helps infants and children use knowledge acquired from statistical learning to make predictions, above and beyond other stimuli. Adults, on the other

hand, are able to employ their statistical-learning abilities across both action and nonaction contexts. Nevertheless, observing actions seems to elicit a learning benefit that is consistent across development.

Though we made every attempt to match the stimuli in the two conditions on saliency, there could still have been perceptual differences between the Agent and Ghost conditions that could alternatively explain our findings. However, perceptual differences cannot solely explain the observed results, because we found no differences in overall visual attention or predictive fixations between conditions during observation. Secondly, both conditions demonstrated learning during observation, but those in the agent condition specifically reproduced more action pairs and acquired more explicit sequence knowledge than did participants in the ghost condition. This finding suggests that there were qualitative differences in the ways the sequence information was learned in the agent condition that were unlikely to be a result of perceptual saliency.

The role of effects

Observing an agent produce causal effects led to higher rates of verbal knowledge and of reproduction of the action pair, relative to observing the ghost events or the pairs with no effect (both action and ghost). This pattern supports the interpretation that observing actions primarily influences the way in which learned knowledge is subsequently used to modify behavior. Even though participants were uninstructed, observing an actor produce an effect in the world may have automatically induced participants to perceive these events as goal-directed and to attempt to re-create them in the test setting. An alternative explanation, suggestive of lower-level accounts, is that the action effect simply provides additional information and is therefore easier to learn. That is, the action–effect relation contains more information (i.e., A predicts both B and C) than does the action-only pair (A predicts B). In addition, the action–effect contingency contains an additional dimension (i.e., actions and effects vs. only actions). According to the model of sequence learning given by Keele, Ivry, Mayr, Hazeltine, and Heuer (2003), multidimensional learning requires additional attention components that are not required during unidimensional learning. These attentional requirements enhance sequence learning by making the learned information accessible to explicit awareness (Keele et al., 2003).

When we analyzed only correct predictions over time, an interaction effect emerged that revealed that participants in the agent condition demonstrated more correct predictive fixations for the effect than for the no-effect pair, whereas this pattern did not hold for the participants in the ghost condition. However, this interaction effect did not appear when we compared patterns of fixations to both correct and incorrect locations. One possible explanation for this inconsistency is that,

in the absence of a visual effect, participants were free to engage in more visual exploratory behaviors to the other objects, resulting in higher proportions of incorrect fixations for the no-effect than for the effect pair.

Action performance and its relation to prediction

Across conditions, participants were more likely to reproduce the pair associated with an effect than the pair without an effect. In addition, rates of performing the effect pair were correlated with participants' predictive looking for this pair. Specifically, the more accurately that observers predicted the effect pair, the more likely they were to reproduce the effect following observation. Adults and children easily re-create effects that they see in the world when they are explicitly asked to do so; this has been empirically demonstrated in both forced-choice and free-choice designs for simple action–effect contingencies (Elsner, 2007; Elsner & Hommel, 2001). Here, our results provide new evidence that observers could re-create action effects based only on learning transitional probabilities, and they did so in the absence of instruction or any explicit task. These findings suggest that new action knowledge—acquired via observational statistical learning—can be accessed and used for action control when the learned actions are used for producing a desired effect or outcome.

In addition, the participants in the agent condition were more likely to reproduce action pairs than were the participants in the ghost condition. This was not due to a general difference in activity between the two conditions, since those in the agent condition did not simply perform more actions overall. On the basis of the idea that we naturally tend to perceive human behavior as goal-directed, the observers in the agent condition may have automatically attributed meaning to the actor's actions and been more motivated to imitate what they had observed, especially when the action resulted in an effect (Hopper, 2010; Hopper et al., 2015). Alternatively, consistent with the faster emergence of correct anticipations in the agent condition, these participants may have also been better able to retain the new knowledge gained from the observed sequence and to apply it when performing their own action sequences than those in the ghost condition.

Relations between predictive gaze, action performance, and verbal knowledge

Whether statistical learning engages implicit or explicit processes—and whether the resulting knowledge is also implicit or explicit—is an ongoing debate (see Daltrozzo & Conway, 2014, for a review). In the present study, we measured predictive gaze, action performance, and verbal responses as reflecting different learning outcomes. These behaviors may

also relate to varying levels of implicit and explicit knowledge of the learned structure. Studies on SL typically demonstrate that the outcomes of learning, and thus the learning processes, are manifested in implicit behaviors such as anticipatory gazes, if at all (Fiser & Aslin, 2001; Perruchet & Pacton, 2006; Turk-Browne et al., 2008). Currently, there is a divide between those who argue that SL is an implicit mechanism (e.g., Clegg, DiGirolamo, & Keele, 1998) and those who suggest that though the process may be implicit, the knowledge obtained via SL can become explicit, when, for instance, learning reaches a certain threshold (Cleeremans, 2006). In the former case, it is argued that knowledge can only become explicit when other cognitive systems come into play. Recent findings have shown that sequence learning also results in explicit knowledge depending on the “task set”—that is, the relation between the stimulus characteristics and the required response of the learner (Esser & Haider, 2017a, 2017b).

Consistent with these recent findings, our data suggest that observing action sequences results in both implicit and explicit learning outcomes.⁵ One possibility, grounded in predictive accounts of the motor system, is that the knowledge gained via statistical learning can be accessed by the motor system and used to update internal action models. These models serve to generate predictions about the most likely upcoming action and provide opportunity to prepare appropriate motor responses. Our findings differ from prior research in that, in the present experiment, no response was required from participants during observation. Thus, the resulting explicit knowledge did not arise from learned stimulus–response associations (as in Haider et al., 2014). Rather, observation alone was sufficient to elicit both implicit and explicit knowledge. Furthermore, our findings suggest that observing human actions facilitates both implicit sequence learning (indicated by faster learning rates in the agent condition) and transferring learned knowledge into explicit responses. However, as was suggested by Schubotz (2007), motor-based learning and prediction can still occur for external events (i.e., nonactions). A fascinating question for further research will be whether observing action sequences engages learning processes entirely distinct from other forms of observational learning, or whether the difference mainly lies in how the knowledge is accessed and used. Another possibility to be considered is that acting immediately prior to being questioned by the experimenter may have influenced some participants' verbal knowledge. That is, action performance may have helped them verbalize knowledge that otherwise would have remained implicit. However, if there were an effect of acting on participants' explicit knowledge of the sequence, this should have been

⁵ Because we did not directly measure the learning processes, but rather the learning outcomes, we cannot speak to whether or not the learning processes themselves were implicit or explicit, and focus our discussion on the outcomes of learning.

consistent across conditions. Instead, the dramatic group differences in verbal knowledge that we observed suggest that responses were primarily influenced by the action observation condition, rather than by their own action production.

Conclusion

In the present study we investigated whether SL abilities can support online prediction during action observation. In particular, we compared observers' sensitivity to statistical regularities in action sequences when observing a human actor relative to visual events. Our main finding revealed that implicit learning occurred in both observation conditions and was not dependent on action effects; however, explicit knowledge was only consistently extracted when observers viewed a human actor perform action sequences with causal effects. These findings shed light on the potential role of the motor system in enhancing how information learned solely via observation can be accessed and used to modify behavior.

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