



# Dynamic development of intuitions and explicit knowledge during implicit learning

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## ABSTRACT

Implicit learning refers to learning without conscious awareness of the content acquired. Theoretical frameworks of human cognition suggest that intuitions develop based on incomplete perceptions of regularity during implicit learning and, in turn, lead to the development of more explicit, consciously-accessible knowledge. Surprisingly, however, this putative information processing pathway (i.e., implicit learning → intuition → explicit knowledge) has yet to be empirically demonstrated. The present study investigated the relationship between implicit learning, intuitions, and explicit knowledge using a modified Serial Reaction Time Task. Results indicate that intuitions of implicitly-learned patterns emerge prior to the development of explicit knowledge. Moreover, intuition timing and accuracy were significantly associated with accuracy of explicit reports. We did not, however, find that stronger implicit learners developed more accurate intuitions. Our findings suggest a crucial role of intuition in the formation of explicit knowledge from implicit learning.

## 1. Introduction

One of the essential adaptations in the evolution of the brain – including human brains – is the capacity to learn and make predictive inferences on the basis of environmental patterns (Clark, 2013). When such learning occurs without conscious awareness, the learning is commonly described as being “implicit” (Reber, 1989). Implicit learning has been implicated in language development (Aslin & Newport, 2012; Saffran, Aslin, & Newport, 1996), visual perception (Rosenthal, Andrews, Antoniadis, Kennard, & Soto, 2016), the capacity to understand and appreciate music (Rohrmeier & Widdess, 2017), religious belief (Weinberger et al., 2020), and mastering sequences of movements (Nissen & Bullemer, 1987; Willingham, 1999).

Although the defining characteristic of implicit learning is that it occurs non-consciously, decades of research have clearly indicated that humans are able to acquire explicit knowledge of implicitly-learned information (Cleeremans & Jiménez, 2002; Destrebecqz & Cleeremans, 2001; Esser & Haider, 2017; Overgaard, 2018; Reber, 1989; Robertson, 2007; Rose, Haider, & Buchel, 2010; Song, Marks, Howard Jr, & Howard, 2009). Here we define explicit knowledge as a state that closely resembles “access consciousness”, when information or knowledge is reportable and/or able to be used for reasoning or justifying

behavior (Block, 1995; Overgaard, 2018; Sandberg, Timmermans, Overgaard, & Cleeremans, 2010; Seth, Dienes, Cleeremans, Overgaard, & Pessoa, 2008). That is, the defining feature of explicit knowledge is that such knowledge is able to be reported and described. The relationship between implicit and explicit knowledge – as well as the process by which information moves between these two states – has been the subject of considerable inquiry.

According to one perspective – often referred to as the “single system” view – there is no distinction between explicit and implicit representation. Rather, implicit knowledge becomes explicit through a strengthening of associations (Cleeremans & Jiménez, 2002; Destrebecqz & Cleeremans, 2003; Esser & Haider, 2017). By contrast, other models indicate distinct but interrelated information processing systems (e.g., System 1 vs. System 2; Kahneman, 2003; Stanovich & West, 2000) with putatively different functions (Cleeremans, 2006; Cleeremans & Jiménez, 2002; Evans, 2003; St. Evans, 2008). Crucially, because information can move between these systems (Esser & Haider, 2017; Haider & Frensch, 2005; Rose et al., 2010; Wessel, Haider, & Rose, 2012), an intermediate “stage” may be needed to create metacognitive judgements, which in turn may render implicitly-learned information explicit.

Consistent with the existence of an intermediate stage, a number of

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accounts of human information processing suggest that implicitly-learned information does indeed become explicit by way of an additional knowledge state: intuition. While several compatible definitions for intuition have been offered (Hodgkinson, Langan-Fox, & Sadler-Smith, 2008), one generally-agreed upon characteristic of intuition is the sense of “knowing without knowing how one knows” (Epstein, 2010; Shirley & Langan-Fox, 1996). Intuitions are believed to develop from implicit learning of information structure/regularity and probabilistic associations (Bowers, Regehr, Balthazard, & Parker, 1990; Hodgkinson et al., 2008; Lieberman, 2000). Thus, intuitions are a product of implicit learning (Dienes & Perner, 1999; Reber, 1989), and manifest as subjective experiences such as gut feelings (Hodgkinson et al., 2008) or tacit knowledge (Reber, 1989). In turn, intuitions can influence subsequent explicit beliefs, knowledge, and behaviors (Greenwald et al., 2002; Kahneman, 2003). According to these accounts, there is a temporally directional relationship between knowledge formation stages: implicit learning precedes intuitions, which emerge prior to explicit knowledge. The present study empirically tested this theoretical framework, investigating the hypothesis that intuitions develop from implicit learning and facilitate explicit awareness.

One of the most frequently used paradigms to measure implicit learning is the Serial Reaction Time Task (SRTT; Nissen & Bullemer, 1987). Although there are many SRTT variations, the basic structure of the task is relatively consistent: participants are instructed to respond quickly and accurately to targets that appear at different locations onscreen by pressing buttons that correspond to those locations. At various times during the task, the targets appear in a complex repeating pattern and, at other times, targets appear randomly. Implicit learning is operationalized as the difference between responding on random vs. patterned presentations, such that scores distinguish responding that is due to actual implicit learning of the patterns from responding due to confounding influences such as motivation, fatigue, or task familiarity (Robertson, 2007). Implicit learning varies widely across participants, and SRTT performance is frequently studied as an individual difference variable (e.g., Howard & Howard, 2001; Howard Jr & Howard, 1997; Kalra, Gabrieli, & Finn, 2019; Song et al., 2009).

Different variations of the SRTT can be classified based on whether they involve a deterministic or probabilistic pattern sequence. In the classical SRTT, patterns are deterministic, meaning that the presentation of targets follow a predetermined pattern. For example, in a 4-target version of the classical SRTT, a pattern of “1–3–2–4” may appear at different points during the task. By contrast, target stimuli in the Alternating Serial Reaction Time task (ASRT; Howard Jr & Howard, 1997) rely on probabilistic pattern sequences. Thus, an ASRT corollary to the deterministic pattern would be “1-r-3-r-2-r-4-r”, where “r” indicates a randomly selected target from one of the four possible target locations. During the ASRT, implicit learning reflects differences in responding to higher probability structures such as “1-[any target]-3” (which can occur when a random target falls between the predetermined targets in the first and third position, *and* when any predetermined target is bookended by  $r = 1$  and  $r = 3$ ) relative to lower probability structures like “2-[any target]-3” (which can only occur when a predetermined target is bookended by  $r = 1$  and  $r = 3$ ).

Critically, a growing body of work has indicated that learners can obtain varying levels of explicit awareness during the *deterministic* SRTT (Esser & Haider, 2017; Haider, Eichler, & Lange, 2011; Haider & Frensch, 2005; Haider & Rose, 2007; Verleger, Seitz, Yordanova, & Kolev, 2015; Willingham & Goedert-Eschmann, 1999; Yordanova et al., 2008; Yordanova, Kirov, & Kolev, 2015) but not the *probabilistic* ASRT (Howard Jr & Howard, 1997; Kóbor et al., 2021). The extent to which explicit awareness during the deterministic SRTT occurs is influenced by trial duration (i.e., extended exposure to patterns increases opportunity for explicit awareness; Reber, 2013; Willingham, 2001) as well as the time interval between when the participant makes a key press and when the next target appears (i.e., shorter intervals limit opportunities to search for patterns and, in turn, obtain explicit awareness; Destrebecqz

& Cleeremans, 2001; Reber, 2013). Another factor that can influence explicit awareness is whether participants are instructed that the targets may follow a pattern. For example, some experimenters have changed visual features of the targets to indicate when they appear in a pattern and when they appear randomly (Miyawaki, 2012; Rüsseler, Munte, & Wiswede, 2018). Other experimental designs include training runs in which participants are instructed on the specific patterns that will occur during the task (Batterink, Reber, & Paller, 2015). When participants obtain explicit awareness of patterns, RT differences between pattern and random blocks are increased (Esser & Haider, 2017; Haider et al., 2011; Haider & Rose, 2007), but the act of *searching* for a pattern may be deleterious (Batterink et al., 2015; Fletcher et al., 2005; Howard & Howard, 2001; but see Horváth, Török, Pesthy, Nemeth, & Janáček, 2020 for evidence that divided attention does not influence learning during the probabilistic ASRT).

Some have argued that the deterministic SRTT is not a task of implicit learning due to the wide range of conditions under which individuals can obtain explicit awareness and because learning can be altered by external variables or top-down influences (Shanks, 2005; Vadillo, Konstantinidis, & Shanks, 2016). Indeed, extensive efforts have been made to isolate implicit learning and enable experimental inferences about explicit awareness without revealing to participants that patterns may occur, as doing so can disrupt implicit learning (Fu, Dienes, & Fu, 2010a; Fu, Dienes, & Fu, 2010b; Haider & Rose, 2007; Norman & Price, 2010; Rose et al., 2010; Rüniger & Frensch, 2008; Wessel et al., 2012).

We take a different perspective. First, “process-pure” implicit learning is not theoretically or empirically supported (Aru & Bachmann, 2017; Huang et al., 2017; Overgaard, 2018; Rose et al., 2010; Sergeant, 2018; Sun, Merrill, & Peterson, 2001; Sun, Slusarz, & Terry, 2005; Sun & Zhang, 2004); different neurocognitive systems are differentially involved based on the extent of conscious processing, but the systems are unlikely to be fully dichotomous. Second, in a practical sense, it is evident that implicit learning frequently occurs alongside more conscious and effortful cognitive operations outside the laboratory. For instance, when learning a new language (especially as an adult), the acquisition of grammatical and structural rules is generally regarded as largely implicit (Aslin & Newport, 2012; Ellis, 1994; Ellis, 2009; Robinson, 1997). In turn, implicitly learned content eventually becomes explicit, confirming the initial expectation of grammatical structure. Experimental work using a dual-task paradigm has demonstrated implicit learning rates are disrupted when individuals are asked to listen to sentences (i.e., syntactic processing) but not when implicit learning is paired with a word recognition or arithmetic task, suggesting that a domain-general implicit learning mechanism contributes to sentence processing (Nemeth et al., 2011). Similarly, learning or listening to music relies on implicit learning of structure, melody, and rhythm (Grahm & Rowe, 2013; Krumhansl & Keil, 1982; Krumhansl, Louhivuori, Toivianen, Järvinen, & Eerola, 1999; Rohrmeier & Widdess, 2017), even though listeners are aware of – and may be looking for – these characteristics of music composition. Thus, rather than a shortcoming, the potential for acquisition of explicit knowledge during the deterministic SRTT – and the fact that implicit learning may occur in concert with explicit search – makes it ideally suited to explore how implicit information can become explicit. Since the primary questions of the present study concern how implicitly-learned information can become explicit, we used a modified version of the *deterministic* SRTT.

Implicit learning is a neurocognitive mechanism that underscores a wide range of mental operations and behaviors. Crucially, however, implicit processes are not fully separable from explicit ones. According to a number of extant perspectives, intuitions facilitate explicit knowledge of implicitly-learned content. That is, implicit learning gives rise to intuitions, which, in turn, bring about explicit knowledge. Somewhat surprisingly, however, there is presently little experimental work to support intuitions based on implicit learning, and the role of intuition in the development of more explicit knowledge is largely untested.

Although individual differences in implicit learning are well-documented, the downstream effects of such variation remain poorly understood. That is, do stronger implicit learners develop more accurate intuitions? Similarly, do more accurate intuitions yield more accurate explicit knowledge?

Here, we addressed these outstanding questions using a modified deterministic Serial Reaction Time Task in which participants were asked to self-report intuitions and explicit knowledge of block structure (i.e., pattern or random). We hypothesized that implicit learning precedes intuitions (H1). That is, we predicted that, during the implicit learning task, participants would develop intuitions after showing evidence of implicit learning. This hypothesis is related to, but distinct from H2: stronger implicit learners form more accurate intuitions. Whereas H1 concerns only the temporal arrangement of implicit learning and intuitions, H2 includes the prediction that individual differences in implicit learning will be associated with variability in the formation of intuitions. Results consistent with *both* H1 and H2 would provide the strongest support for the formation of intuitions based on implicit learning. Additional hypotheses concerned the relationship between intuitions and explicit knowledge – specifically, that intuitions emerge prior to explicit knowledge (H3), and that better intuitions (i.e., faster, more accurate) lead to better explicit knowledge (H4). Additional exploratory analyses examined the effects of explicit knowledge on sequence learning (i.e., differences in RT for pattern and random conditions over time). The hypotheses, methods, and analytic framework for the present study were preregistered on the Open Science Framework prior to data collection (<https://osf.io/4pjmz>).

## 2. Method

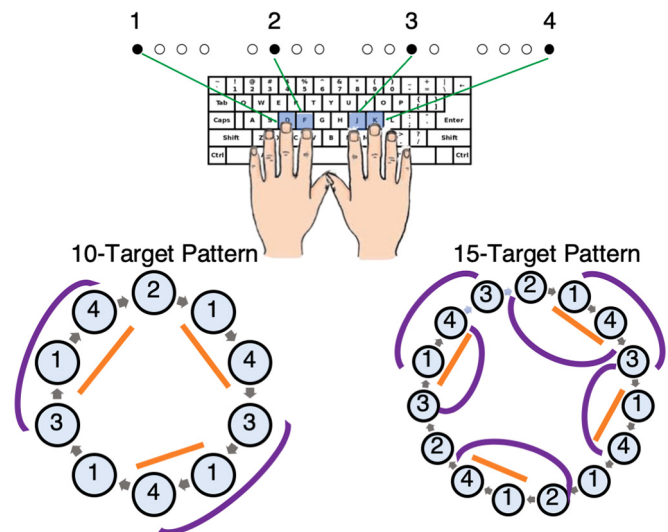
### 2.1. Participants

One hundred and sixty-six participants completed the study online through *Prolific*. The validity of online data collection has become an important topic of inquiry in behavioral science, and recent evidence indicates that *Prolific* offers higher quality data (e.g., based on participant attention and honesty) and a more diverse participant pool compared to alternative online research platforms, such as Amazon Mechanical Turk (Palan & Schitter, 2018; Peer, Brandimarte, Samat, & Acquisti, 2017). The experiment was designed with Gorilla (<https://gorilla.sc/>), an online behavioral experiment builder that allows for accurate recording of participant RT (Anwyl-Irvine, Massonnié, Flitton, Kirkham, & Evershed, 2019). Participants provided informed consent, and all study procedures were approved by the Georgetown University IRB. Participants were paid \$7.50. Following careful quality control of participant data (see Supplementary Information), the final sample consisted of 121 participants ( $M_{age} = 28.45$ ,  $SD = 8.92$ ; 58.58% male, 40.50% female), in line with a priori power considerations.

An additional group of participants (“confirmatory sample”) were also recruited online through *Prolific* to directly investigate the temporal relationship between intuitions and explicit knowledge. That is, do intuitions precede explicit knowledge? Study procedures for this sample ( $N = 42$ ,  $M_{age} = 25.42$ ,  $SD = 8.31$ ; 76.19% male, 23.81% female, see Supplementary Information) are described at the end of the Method section.

### 2.2. Serial reaction time task

Participants completed a modified version of the deterministic Serial Reaction Time Task (SRTT), a widely-used implicit learning paradigm. In the present version of the SRTT, target circles (henceforth referred to as “targets”) appeared in one of four positions arrayed horizontally onscreen (Fig. 1). Each target corresponded to a specific key on the keyboard. Participants were instructed on the target-key mappings, and were told to press the appropriate key as accurately and quickly as possible when each target appeared onscreen. The defining feature of



**Fig. 1. Serial reaction time task.** Participants indicated target locations by pressing the corresponding key. For example, a target in the left most location was associated with the “D” key (Position 1). During the uninstructed learning phase, pattern blocks consisted of a 10-target repeating pattern (repeated 10×), comprised of three first-order structures (orange bar) and two second order structures (purple bar). During the instructed learning phase, participants completed three 10-target pattern blocks and two 15-target pattern blocks, which also consisted of first-order (orange bar) and second-order (purple bar) structures. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

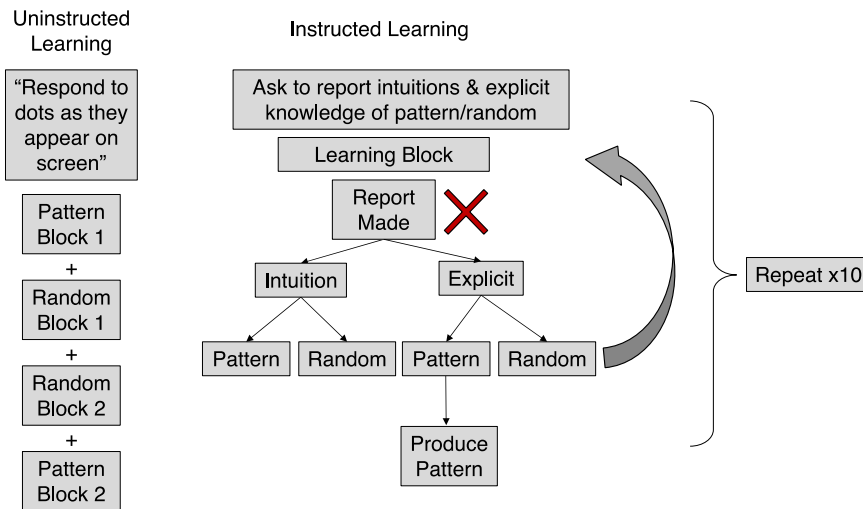
the SRTT is that, at various times during the task, the targets appear in a repeating pattern and, at other times, appear randomly. Patterns are designed to elude explicit awareness – at least initially – and implicit learning is operationalized as the difference in responding (based on RT) on pattern and random sections of the task to differentiate changes in RT based on implicit learning from those based on confounding influences.

Notably, some participants may consciously search for embedded patterns during the SRTT, regardless of whether they are instructed to do so. The literature is somewhat mixed with respect to the effect of explicit search during the deterministic SRTT, although a reasonably well-replicated collection of studies have demonstrated that searching does not lead to faster responding and may actually harm performance (Fletcher et al., 2005; Howard & Howard, 2001; Reber, 2013). Regardless of whether searching is ameliorative or deleterious, the opportunities for – and effect of – explicit search on the SRTT can be mitigated by shortening the response-stimulus-interval (RSI), the delay between when a participant makes a correct key press and the presentation of the subsequent target. While early versions of the SRTT had an RSI of approximately 250 ms (Destrebecqz & Cleeremans, 2001; Nissen & Bullemer, 1987), the next target in the present study appeared *immediately* after participants pressed the corresponding key. This so-called “no-RSI” version of the SRTT significantly reduces the extent to which participants can search for patterns because the next target appears immediately after a correct button-press, thereby eliminating the opportunity for participants to use the inter-stimulus-interval to anticipate the next target and explicitly learn the pattern structure (Destrebecqz & Cleeremans, 2001).

After receiving task instructions, participants completed a 44-target practice block in which the targets appeared randomly. They then advanced through two phases of the SRTT (described below; Fig. 2). The entire SRTT paradigm is freely available for use at: <https://app.gorilla.sc/openmaterials/268426>.

#### 2.2.1. Phase 1: Uninstructed learning phase

Following practice, participants performed the “uninstructed



**Fig. 2. SRTT study design.** Participants completed 4 uninstructed learning blocks (Left; order counterbalanced) before receiving additional instructions. The instructed learning phase of the study (Right) consisted of 10 blocks (also counterbalanced), during which participants were tasked with making self-reports to indicate intuitions and/or explicit knowledge. After a self-report, participants returned to the learning block. Each block ended after the 105th target, regardless of the number of self-reports made.

learning” phase of the experiment, which consisted of four 100-target blocks (2 pattern, 2 random), with order counterbalanced. The two pattern blocks each contained a distinct 10-target repeating pattern, which consisted of three first-order structures and two second-order triplets (Fig. 1). First and second-order structures are consecutive targets that occur at a high frequency over the course of a block. The appearance of the first target of a structure (e.g., Position 1 in the 10-target pattern in Fig. 1) is associated with greater likelihood of an ensuing target (e.g., Position 4 appears following Position 1 75% of the time). Implicit learning, therefore, is likely to depend on participants’ ability to detect these recurring structures (Song, Howard, & Howard, 2007, 2008). Random blocks did not include regular repetitions (see SI for more information about creation of random blocks). Notably, the uninstructed learning phase was completed before participants received information about the possible presence of patterns. Learning during this phase was therefore likely to be less influenced by top-down processes compared to the instructed learning blocks.

### 2.2.2. Phase 2: Instructed learning phase

Following completion of the uninstructed learning phase, participants were informed that the targets may appear in a pattern and that at other times the targets would appear randomly. Additional text indicated that, at different points during the task, they may develop intuitions (“you may have a sense that [there might be a pattern/dots might be appearing randomly] but may not be sure why you feel that way”) and explicit knowledge (“clear knowledge that the dots [are following a pattern/appearing randomly]”). Participants were instructed to self-report the precise moment at which they developed an intuition and/or explicit knowledge by pressing a “stop key” (“Y” on the keyboard). Upon making a self-report, participants were immediately directed to a separate screen to indicate (1) whether they had an intuition or explicit knowledge and (2) whether they were reporting a pattern or randomness. If they reported explicit knowledge of a pattern, participants were asked to reproduce it. After providing this information, participants were redirected back to the same block and were permitted to stop the block again at any point. Participants could report explicit knowledge prior to reporting an intuition, thus allowing for an empirical assessment of whether intuitions emerged before explicit knowledge. The instructed learning phase consisted of 10 blocks (5 pattern, 5 random) with 105 targets each. Pattern blocks were distinct from the pattern blocks in the uninstructed phase. All blocks ended after the 105th target.

We were interested in both timing and accuracy of self-reports. Self-report timing (i.e., when a participant indicated an intuition or explicit knowledge) was scored based on the target number in the block when

the report was made, such that lower values indicated an earlier report. For example, a participant who reported an intuition on the 30th target and explicit knowledge on the 80th target would have timing scores of 30 for intuition and 80 for explicit knowledge for that block. Timing information was averaged across all the blocks, resulting in an average timing score for intuitions and an average timing score for explicit knowledge for each participant. Self-report accuracy (i.e., whether a participant’s report of a pattern or randomness was correct) was scored using a discriminability index, in which correct responses were coded as 1 (i.e., participant self-reported a pattern during a pattern block, or random during a random block), incorrect responses as −1 (i.e., participant self-reported a pattern block as being random, or vice-versa), and no-response as 0 (i.e., a block in which a self-report was not made). Separate average accuracy indices were obtained for intuitions and explicit knowledge for each participant (see SI for more detailed scoring information on self-report timing and accuracy).

Finally, following an explicit report of a pattern, participants were asked to reproduce the pattern (henceforth, “pattern recall”). Pattern recall was scored in accordance with prior work on explicit recall for the SRTT (Willingham & Dumas, 1997). Specifically, pattern recall was based on the reported number of correct, contiguous elements of the repeating pattern, starting/ending anywhere within the repeating pattern. For example, in the case of the 10-target pattern in Fig. 1, a participant who entered the pattern “1–4–2–3–2–1–3–1” would have received a score of 6, because “1–4–2” and “1–3–1” are both included in the sequence (note that at least 3 continuous targets are required, so “2–1” is not scored; Willingham & Dumas, 1997). Similarly, a participant who entered “3–1–4–2–1–4” would have a score of 6 as well. Scores for all five patterns were summed for an overall pattern recall score.

### 2.3. Analytic strategy

Implicit learning was measured using mixed effects models, consistent with recent work on sequence learning (Kahn, Karuza, Vettel, & Bassett, 2018; Karuza, Kahn, & Bassett, 2019). Mixed effects models can account for within and between subject effects, and are appropriate when several repeated measurements (Level 1) are nested within a higher level of data (Level 2; Goldstein, 2011; Longford, 1995). In the present study, target-level information (e.g., target number within the block, block condition) were modeled as Level 1 variables, nested within each participant; Level 2). All mixed effects models (described in detail below) were fit via maximum likelihood and unstructured variances and covariances, using the mixed command in STATA 15 (Stata, 2017). Significance tests were two-sided. Because learning during the uninstructed and instructed blocks were performed under different task

demands, we performed separate mixed effects models for these two phases of the experiment. Detailed model information can be found in Supplementary Information.

### 2.3.1. Uninstructed learning phase

Implicit learning during the uninstructed learning phase was calculated by fitting a mixed effects model in which RT (for each individual target) was positioned as the dependent variable, with the following Level 1 independent variables: target number (i.e., 1 to 100), block condition (pattern or random), and corresponding button (D, F, J, K). Crucially, all models also included a Target Number X Block Condition interaction term, which indicated the extent to which learning rate (based on changes in RT over the course of the block) varied as a function of block condition. That is, the interaction term provided an estimate of implicit learning. Note that RT differences in Block Condition alone (i.e., without an interaction with Target Number) reflect differences in the *average* RT between the two conditions and do not account for how the RT discrepancy changes as individuals advance through each block. Because we anticipated that participants would become faster on the pattern blocks over time (i.e., RT decrease with successive targets), we modeled implicit learning by calculating the extent to which the change in RT over time differed between block conditions (i.e., a Target Number X Block Condition interaction). The first 10 targets for each block were excluded to allow for a brief familiarization. We also excluded all targets with an RT > 1000 ms or RT < 200 ms as well as those for which a participant made an incorrect button press.

### 2.3.2. Instructed learning phase

We fit three different mixed effects models for the instructed learning phase to test different hypotheses about implicit learning, intuitions, and explicit knowledge. In addition to what is described below, all instructed learning phase models included an additional covariate regressor – “Lag Time” – to control for any aberrant delays between when a participant made a correct button-press and the appearance of the next target (see Supplementary Information for more discussion of this variable).

**2.3.2.1. Instructed implicit learning.** Instructed implicit learning was investigated by constraining the analyses to targets *prior* to the first self-report in each block because responding after a self-report was no longer “fully” implicit (i.e., because the participant indicated an intuition or explicit knowledge). A Target Number X Block Condition interaction term was again used to measure implicit learning. In order to partially control for implicit learning differences based on the number of Level 1 data points (e.g., a participant who made a self-report on the 30th target would have fewer Level 1 data points compared with a participant who self-reported on the 60th target), the model also included an additional Level 1 covariate that indicated, for each participant at each block, how many targets were presented before the first self-report.

**2.3.2.2. Self-report effect on sequence learning.** A second mixed effects model examined the extent to which the first self-report influenced sequence learning (i.e., differences in RT for pattern and random conditions over time) during the SRTT. In other words, does sequence learning improve with greater explicit awareness? Note that for this model we refer to “sequence learning” rather than “implicit learning” because we are examining RT differences between pattern and random blocks after a self-report was made (i.e., when learning was no longer implicit). This question was explored using an additional three-way interaction term – Target Number X Block Condition X Self-Report – that indicated the extent to which learning rate (i.e., Target Number X Block Condition) changed following a self-report.

**2.3.2.3. Differences in implicit learning based on intuition accuracy.** A third mixed effects model investigated the relationship between implicit

learning and intuitions (i.e., H2). Here, we constrained analyses to before the first intuition self-report for each participant at each block (i.e., while learning was still implicit). A Level 1 dummy variable – Intuition Accuracy – coded each Level 1 data point based on whether the participant self-reported a correct or incorrect intuition for each block (blocks for which a participant did not make a self-report were excluded from this model). This variable was then used in an additional three-way interaction (Target Number X Block Condition X Self-Report Accuracy), with the coefficient of this interaction term reflecting the extent to which implicit learning (i.e., Target Number X Block Condition) varied based on intuition accuracy. In this case, a significant effect would indicate differences in implicit learning based on intuition accuracy.

### 2.4. Confirmatory sample procedures

One of the primary research questions of the present study concerned the temporal relationship between intuitions and explicit knowledge. Said simply, do intuitions develop before explicit knowledge? Although participants in the main sample were provided with specific definitions for these two terms, it is plausible that participants may have entered the study with preconceived definitions about explicit knowledge and/or intuition. That is, they may have inferred or assumed that intuitions come first.

A small confirmatory sample was recruited in order to rule out this alternative explanation. For this sample, half of the participants received instructions for how to report intuitions while the other half were instructed on how to report explicit knowledge. In other words, participants were made aware of – and asked to indicate – only one type of knowledge. At the midway point of the study, participants received instructions on how to report the alternative type of knowledge (e.g., participants who were first asked to report intuitions received instructions on reporting explicit knowledge). This design allowed us to examine differences using both a within subject (i.e., comparing timing of judgements for intuitions and explicit knowledge) and between-subject design (examining timing differences based on task instruction during the first half of the instructed learning phase).

## 3. Results

### 3.1. Confirmatory sample: temporal relationship of intuitions and explicit knowledge

We hypothesized that intuitions precede explicit knowledge (H3). Results from the confirmatory sample were consistent with this hypothesis. A paired samples *t*-test indicated a significant within-subject effect, such that participants reported intuitions ( $M_{\text{Target}} = 51.39$ ,  $SD = 22.02$ , 95% CI [44.53–58.25]) earlier than explicit knowledge ( $M_{\text{Target}} = 67.88$ ,  $SD = 22.588$ , 95% CI [60.84–74.91];  $t(41) = -5.14$ ,  $p < 0.0001$ ). Similarly, a two-sample *t*-test with unequal variances revealed a significant between-subject effect of instruction type ( $t(39.96) = 2.70$ ,  $p = 0.01$ ), demonstrating that participants told to self-report intuitions ( $M_{\text{Target}} = 50.34$ ,  $SD = 23.41$ , 95% CI [40.49–60.26]) did so earlier than those told to self-report explicit knowledge ( $M_{\text{Target}} = 67.64$ ,  $SD = 17.97$ , 95% CI [58.70–76.68]). Taken together, results from this sample are in line with the hypothesized temporal relationship of intuitions and explicit knowledge (i.e., intuitions come first). Further, these results argue against the interpretation that differences in intuition and explicit knowledge timing in the main sample would stem from participants’ pre-existing beliefs about intuitions and explicit knowledge.

### 3.2. Uninstructed implicit learning

All participants performed an uninstructed learning phase of the SRTT in which they completed four 100-target blocks, of which two contained a unique 10-target repeating pattern. Learning rates for

pattern and random blocks are displayed in Fig. 3A. Results indicated clear evidence of implicit learning; we observed a significant Target Number X Block Condition interaction (estimated effect: 0.45,  $z = 8.94$ ,  $p < 0.001$ ; Table 1), such that participants responded increasingly fast during the pattern blocks relative to the random blocks (see SI for learning rates using accuracy data). Participant-level estimates for implicit learning were retained for use in subsequent analyses. Finally, split-half analysis was performed to test the reliability of uninstructed implicit learning. Specifically, we ran two separate mixed models, with each model including only half of the total targets (randomly selected). Participant-level implicit learning estimates obtained from these two models were strongly correlated with uninstructed implicit learning calculated from the full set of targets (both  $r > 0.74$ ,  $p < 0.0001$ ) and with each other ( $r = 0.46$ ,  $p < 0.0001$ ), indicating good reliability.

### 3.3. Instructed implicit learning

After completing the uninstructed learning phase, participants were informed that, at different points during the remainder of the task (i.e., the instructed learning phase), the targets would appear in a complex pattern. Additionally, they were asked to self-report when they developed intuitions and/or explicit knowledge. Consistent with findings from the small confirmatory sample, paired  $t$ -tests revealed that participants reported intuitions ( $M_{\text{Target}} = 65.27$ ,  $SD = 19.10$ , 95% CI [61.84–68.71]) earlier than explicit knowledge ( $M_{\text{Target}} = 86.94$ ,  $SD = 13.70$ , 95% CI [84.48–89.40];  $t(120) = -11.03$ ,  $p < 0.0001$ ; see SI for distribution of these variables). Thus, as hypothesized (H3), intuitions preceded explicit knowledge. Self-report accuracy was also greater than chance (0) for both intuitions ( $M_{\text{Index}} = 0.24$ ,  $SD = 0.29$ , 95% CI [0.19–0.29];  $t(120) = 9.41$ ,  $p < 0.0001$ ) and explicit knowledge ( $M_{\text{Index}} = 0.21$ ,  $SD = 0.23$ , 95% CI [0.17–0.25];  $t(120) = 10.16$ ,  $p < 0.0001$ ; SI), indicating that participants were able to accurately assess their own awareness of block structure.

To investigate instructed implicit learning, we restricted our analyses to the targets for each block that occurred *prior* to the first self-report. For example, if a participant made a self-report on the 30th target of a given block, we examined targets 1–29 for that block for that participant. Analyses were further constrained to include only blocks for which a participant made a self-report.

A mixed effects model revealed that, even with the additional instructions that preceded the instructed phase of the SRTT, participants were able to implicitly learn the patterned structure (Fig. 3B). That is, we observed a significant Target Number X Block Condition interaction before participants made a self-report (estimated effect = 0.30,  $z = 3.56$ ,  $p < 0.001$ ; Table 2). To test the reliability of instructed implicit learning, we conducted another split-half analysis, which revealed excellent reliability (associations between each “split-half” implicit learning estimate and full model estimate: both  $r > 0.93$ ,  $p < 0.0001$ ; correlations

**Table 1**

Mixed effects model for implicit learning during uninstructed learning phase (fixed effects).

| Reaction Time                              | Estimate | Std. Err. | z     | p      | 95% Conf. Interval |        |
|--------------------------------------------|----------|-----------|-------|--------|--------------------|--------|
| Target Number †                            | −0.03    | 0.04      | −0.78 | 0.435  | −0.11              | 0.05   |
| Block Condition Random♣                    | 9.00     | 1.70      | 5.29  | <0.001 | 5.67               | 12.33  |
| IL: Target Number X Block Condition Random | 0.45     | 0.05      | 8.94  | <0.001 | 0.35               | 0.55   |
| Button                                     |          |           |       |        |                    |        |
| F                                          | 40.28    | 1.41      | 28.54 | <0.001 | 37.52              | 43.05  |
| J                                          | 32.56    | 1.91      | 17.01 | <0.001 | 28.81              | 36.31  |
| K                                          | −8.83    | 2.48      | −3.56 | <0.001 | −13.70             | −3.96  |
| Intercept                                  | 463.26   | 7.20      | 64.33 | <0.001 | 449.14             | 477.38 |

Note: † effect for patterned blocks, ♣ effect at Target Number 45.5; IL = implicit learning.

**Table 2**

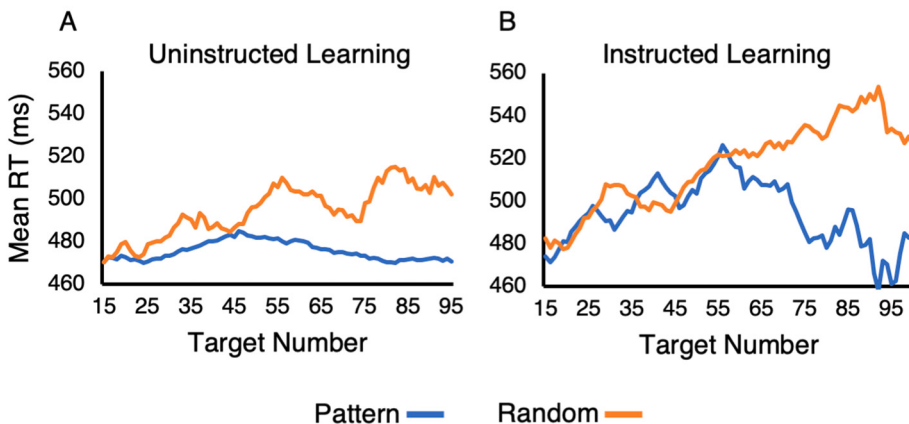
Mixed effects model for implicit learning during instructed learning phase (fixed effects).

| Reaction Time                              | Estimate | Std. Err. | z      | P      | 95% Conf. Interval |        |
|--------------------------------------------|----------|-----------|--------|--------|--------------------|--------|
| Target Number †                            | 0.83     | 0.04      | 20.43  | <0.001 | 0.75               | 0.91   |
| Block Condition Random ♣                   | 9.89     | 1.80      | 5.49   | <0.001 | 6.37               | 13.43  |
| IL: Target Number X Block Condition Random | 0.30     | 0.08      | 3.56   | <0.001 | 0.13               | 0.46   |
| Button                                     |          |           |        |        |                    |        |
| J                                          | 28.75    | 1.54      | 18.62  | <0.001 | 25.72              | 31.78  |
| K                                          | 1.79     | 1.52      | 1.17   | 0.241  | −1.20              | 4.78   |
| Lag Time                                   | −13.44   | 1.53      | −8.80  | <0.001 | −16.44             | −10.45 |
| Number of Targets                          | 4.87     | 1.67      | 2.92   | 0.003  | 1.60               | 8.14   |
| Intercept                                  | −0.43    | 0.04      | −11.95 | <0.001 | −0.50              | −0.36  |
|                                            | 452.36   | 28.10     | 16.10  | <0.001 | 397.30             | 507.43 |

Note: † effect for patterned blocks; ♣ effect at Target Number 53; IL = implicit learning.

across halves:  $r = 0.75$ ,  $p < 0.0001$ ).

It is worth noting, however, that participants displayed a small *increase* in RT for patterned blocks (estimated increase of 0.83 ms at each target), but this increase was significantly less than the increase observed on random blocks (i.e., as indicated by the significant interaction). This may be due to the increased pattern complexity during the



**Fig. 3. Implicit learning during uninstructed and instructed blocks.** Trajectories reflect average RT for the whole sample, smoothed with a 10-window sliding mean. (A) Implicit learning during the uninstructed blocks. (B) Implicit learning (i.e., before first self-report) during the instructed blocks. Differences in learning rate between patterned and random blocks significant for both ( $p < 0.001$ ). Despite differences in RT trajectories, visual inspection indicates similar RT drop-off for patterned blocks around midpoint of learning period.

instructed learning phase or top-down influences – indeed, the overall increase in RT is greater during the instructed learning phase compared with the uninstructed phase (Fig. 3). Another explanation may be that implicit learning was calculated from comparatively fewer targets relative to the uninstructed learning phase (i.e., because participants stopped the block to report knowledge), and with more time on the instructed learning blocks, participants may have become even faster to respond to patterns. Consistent with this interpretation, we found a significant main effect of Number of Targets, such that participants who responded to more targets prior to making a self-report were faster (estimated effect =  $-0.43$ ,  $z = -11.95$ ,  $p < 0.001$ ; Table 2). Finally, the greatest “noise” in RT – for both blocks conditions – occurred towards the end of the uninstructed learning phase (approximately around Target 80 and then again around Target 95; Fig. 3). Given the mean report time of intuitions ( $M_{\text{Target}} = 65.27$ ; as described above), these RT spikes were based only on the data from the small number of participants who self-reported well after the average for the sample (because we only considered RT before a response was made).

Lastly, a paired t-test to compare participant-level estimates of implicit learning during the instructed and uninstructed phases of the study indicated that implicit learning was greater during the uninstructed phase ( $t(120) = 2.47$ ,  $p = 0.02$ , 95% CI[0.03–0.28]), consistent with previous findings that searching for a pattern during the deterministic SRTT (which, presumably, occurred during the instructed phase) impedes implicit learning. Implicit learning was uncorrelated across the two phases ( $r = -0.03$ ,  $p = 0.77$ ), with Bayesian analyses (performed in JASP; Love et al., 2019) indicating the null hypothesis was 8.12 times more likely in this case ( $BF_{01} = 8.12$ ).

### 3.4. Association between implicit learning and intuitions

#### 3.4.1. Uninstructed implicit learning

We hypothesized that stronger implicit learners would have more accurate intuitions (H2). Given recent work demonstrating implicit learning stability across different contexts (Kalra et al., 2019), we first asked whether *uninstructed* implicit learning was correlated with accuracy and timing of intuitions in the *instructed* phase. To be clear, this question concerned whether implicit learning with one set of stimuli (i.e., uninstructed phase) was correlated with the development of intuitions on a separate set of implicitly-learned stimuli (instructed phase). We did not find any evidence in favor of this association (Table 3); better implicit learning in the uninstructed phase was unassociated with intuition timing ( $r = 0.16$ ,  $p = 0.07$ ,  $BF_{01} = 1.83$ ) or accuracy ( $r = -0.09$ ,  $p = 0.32$ ,  $BF_{01} = 5.43$ ).

#### 3.4.2. Instructed implicit learning

We next fit another mixed effects model to more directly test the hypothesis that intuitions develop from implicit learning (H1). Further, we investigated whether stronger implicit learning was associated with more accurate intuitions (H2). Here, we focused specifically on learning during the instructed learning phase before the first self-reported intuition for each participant in each block (i.e., when learning was still implicit), and used a 3-way Target Number X Block Condition X Intuition Accuracy interaction to estimate the extent to which implicit

learning differed based on intuition accuracy, with a significant (and negative) coefficient indicating that stronger implicit learning preceded correct intuitions (relative to incorrect intuitions).

Results from this model revealed that both correct and incorrect intuitions were preceded by implicit learning (Fig. 4B). Thus, consistent with our hypothesis (H1), intuitions were temporally preceded by implicit learning. However, results did not support the hypothesis (H2) that better implicit learning leads to more accurate intuitions. That is, accurate intuitions (relative to inaccurate intuitions) were not preceded by stronger implicit learning (Target X Block Condition X Intuition Accuracy estimated effect =  $0.19$ ,  $z = 1.47$ ,  $p = 0.14$ ,  $BF_{01} = 1.14$ ; Fig. 4, Table S5). Therefore, although implicit learning occurred before participants reported an intuition, it is unclear the extent to which the implicit learning process influenced the formation of intuitions.

### 3.5. Relationship between intuitions and explicit knowledge

Having established that intuitions developed prior to explicit knowledge, we next examined whether accuracy and/or timing of intuitions were associated with explicit knowledge (H4). First, we observed a positive, weak correlation between timing of intuitions and timing of explicit knowledge ( $r = 0.16$ ,  $p = 0.08$ ,  $BF_{01} = 1.83$ ; Table 3). Further, intuition timing was significantly correlated with accuracy of explicit self-reports (i.e., correctly identifying the block structure as either pattern or random;  $r = -0.26$ ,  $p = 0.004$ ). Thus, participants who reported earlier intuitions also reported earlier – and more accurate – explicit knowledge.

In cases in which a participant self-reported explicit knowledge of a pattern, they were asked to type the pattern on the keyboard. We found that pattern recall was significantly correlated with intuition timing (earlier intuitions associated with better pattern recall;  $r = -0.31$ ,  $p = 0.0005$ ) and intuition accuracy ( $r = 0.19$ ,  $p = 0.03$ ). Taken together, these results suggest that the timing and quality of intuitions are associated with explicit knowledge.

### 3.6. Self-report effect on sequence learning

Lastly, we explored whether obtaining more consciously-accessible knowledge influenced sequence learning. In other words, did participants respond increasingly fast on pattern blocks (relative to random) after reporting sequence knowledge? This question was investigated by fitting a mixed effects model with a Target Number X Block Condition X Self-Report interaction term. Results from this model (Table S4), revealed a significant three-way interaction (estimated effect =  $-0.17$ ,  $z = -2.08$ ,  $p = 0.038$ ), with greater sequence learning (i.e., difference in learning rate for pattern and random blocks) after a self-report (Fig. 4A). This result is in line with prior literature demonstrating superior sequence learning with more explicit awareness.

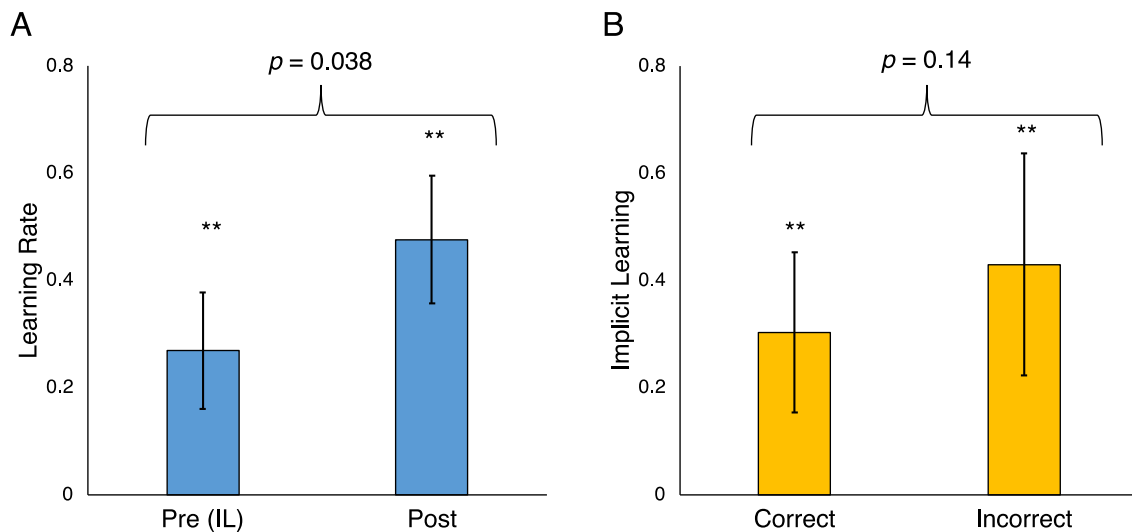
## 4. Discussion

The present study investigated the development of intuitions and explicit knowledge during an implicit learning paradigm. Theoretical accounts of human information processing indicate implicit learning as

**Table 3**  
Correlations between uninstructed implicit learning, intuitions, and explicit knowledge.

|                    | Uninstructed IL | Intuition Timing | Intuition Accuracy | Explicit Timing | Explicit Accuracy |
|--------------------|-----------------|------------------|--------------------|-----------------|-------------------|
| Intuition Timing   | 0.16            | –                |                    |                 |                   |
| Intuition Accuracy | –0.09           | –0.30***         | –                  |                 |                   |
| Explicit Timing    | –0.04           | 0.16             | 0.14               | –               |                   |
| Explicit Accuracy  | –0.01           | –0.26**          | 0.28**             | –0.42***        | –                 |
| Pattern Recall     | –0.04           | –0.31**          | 0.19*              | –0.40***        | 0.63***           |

Note: “Intuition Accuracy” and “Explicit Accuracy” are based on participants’ self-report of pattern structure (see “Method: Phase 2 Instructed Learning Phase”; SI) for a given block. “Pattern Recall” refers to report the number of correct elements of the pattern reported \*;  $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ , uncorrected.



**Fig. 4. Differences in learning rates.** (A) Sequence learning was greater after making a self-report (see mixed effects model; SI). (B) No differences in instructed implicit learning for correct and incorrect intuitions. Note: \*\* indicates significant estimated effect in mixed effects model at  $p < 0.001$ ; 95% CI indicated.

a basis of intuition (Bowers et al., 1990; Epstein, 2010; Hodgkinson et al., 2008; Lieberman, 2000; Reber, 1989; Shirley & Langan-Fox, 1996), and intuition as a precursor to explicit knowledge (Greenwald et al., 2002; Kahneman, 2003). Our results supported some, but not all of this conceptual framework. Consistent with our first hypothesis, we found that intuitions were temporally preceded by implicit learning (H1). However, results did not support our second hypothesis that stronger implicit learners provide more accurate intuitions (H2). Thus, our findings cannot shed light on the bases of individual differences in intuition accuracy (i.e., since they do not appear to stem from differences in implicit learning). Our results do, however, demonstrate that intuitions may be a basis for individual differences in explicit knowledge. We found that participants indicated intuitions prior to explicit knowledge (H3), and that better/earlier intuitions were associated with to more explicit knowledge (H4).

A number of theoretical models highlight the role of intuitions in the process by which implicitly-learned information becomes explicit (Epstein, 2010; Kahneman, 2003; Reber, 1989, 1992). Despite the prominence of intuition-based theories of human cognition, we are unaware of any work that has empirically demonstrated that intuitions are preceded by implicit learning, or that intuitions emerge before – and are associated with – later explicit knowledge. The present findings lend some support to these accounts. First, intuitions emerged after a period of implicit learning. Second, participants who reported earlier intuitions made more accurate explicit reports and, perhaps most notably, were able to recall more pattern elements.

By contrast, results did not support our hypothesis that stronger implicit learners would achieve faster or more accurate intuitions (H2), which challenges prior suggestions that implicit learning is a basis for intuitions or “tacit knowledge” (Reber, 1989). We investigated this hypothesis in two ways. First, given recent work demonstrating some consistency in implicit learning across different experimental paradigms (Kalra et al., 2019), we correlated intuition timing and discriminability with participant-level estimates of *uninstructed* implicit learning. In this way, we asked whether implicit learning of one set of stimuli (i.e., the uninstructed phase) was associated with the development of intuitions in a second set of stimuli (the instructed phase). No such association was identified, and results revealed a trending association for uninstructed implicit learning and intuition timing in the opposite direction (i.e., higher uninstructed implicit learning associated with later intuitions). However, because uninstructed and instructed implicit learning were not correlated in the present study, these null results are somewhat unsurprising.

On the other hand, we were surprised to find that differences in instructed implicit learning were also unrelated to intuition accuracy, particularly because intuitions were temporally preceded by implicit learning. That is, when analyses were constrained to the period of time before self-reports, we still observed clear evidence of implicit learning (i.e., faster responding on the pattern blocks). Had we failed to observe implicit learning before participants made a self-report, one could simply conclude that implicit learning did not occur during the instructed learning phase and, thus, there would be no reason to observe an association between pre-report sequence learning and accuracy of the report. Therefore, because implicit learning *did* occur, it remains an open question as to what mechanism is responsible for variability in the development of intuitions (i.e., since differences in learning rate did not account for this variability within our data set). Parallel, dissociable development of implicit and explicit knowledge during deterministic implicit learning tasks has been well-documented (e.g., Gabrieli, 1998; Nissen & Bullemer, 1987; Willingham, 2001; Willingham & Goedert-Eschmann, 1999; Willingham, Salidis, & Gabrieli, 2002). Given the present finding that intuitions and explicit knowledge are closely related to each other (i.e., better intuitions were associated with better explicit knowledge) but not with implicit learning, it may be more appropriate to consider intuitions as “partial” explicit knowledge rather than stemming from implicit learning. Since implicit and explicit knowledge can develop independently and in parallel, it would therefore not necessarily be the case that variability in implicit learning is associated with variability in intuitions (when considered as partial explicit knowledge).

Alternatively, it is possible that better implicit learners do form faster or more accurate intuitions, but that task demands of the present study – specifically, top-down search during the instructed learning phase – obscured this association. There is growing evidence that explicit search can influence implicit learning on deterministic versions of the SRTT (Fletcher et al., 2005; Howard & Howard, 2001; Reber, 2013), and that obtaining explicit knowledge further influences responding (Esser & Haider, 2017; Haider et al., 2011; Haider & Rose, 2007). However, in devising the present study, we accepted the potential for a certain amount of top-down influence during the instructed learning phase because “real world” implicit learning is often accompanied by a host of additional external factors (Aru & Bachmann, 2017; Aslin & Newport, 2012; Ellis, 1994; Ellis, 2009; Overgaard, 2018; Robinson, 1997; Rose et al., 2010; Sun et al., 2005). We do not assume that the instructed learning phase involved no additional top-down search – indeed our findings indicate that top-down search likely did occur because learning was greater during the uninstructed learning phase. As it relates to the

development of intuitions, however, it is plausible that cognitive demands associated with requiring participants to report multiple kinds of knowledge influenced working memory and/or attention in unintended ways, and that this increased load impacted implicit learning performance (as well as subsequent self-reports). Prior work has demonstrated correlations between working memory and intentional/explicit sequence learning (Bo, Borza, & Seidler, 2009; Bo, Jennett, & Seidler, 2012), putatively because working memory resources are required to direct attention and cognitive control (Janacek & Nemeth, 2013; Kaufman et al., 2010). The influence of working memory on undirected implicit learning is less clear, but appears to be comparatively less than during intentional learning (Janacek & Nemeth, 2013, 2014; Martini, Sachse, Furtner, & Gaschler, 2015). Therefore, working memory capacity may have influenced sequence learning during the instructed learning phase of the present study, such that individuals higher in working memory demonstrated superior learning. This increased influence of working memory may have interfered with a putative association between implicit learning and intuitions.

Since the results of the present study provide reasonably clear evidence that intuitions precede – and are associated with – explicit knowledge, future studies should ask participants to report only one kind of knowledge (i.e., intuitions). Such a paradigm would minimize the burden on working memory (compared to the present study), thereby reducing the potential influence of working memory demand on learning rates and intuitions. This simplified system of self-report would ideally be paired with the ASRT, which contains probabilistic, rather than deterministic, pattern sequences. Learning during the ASRT has been reliably shown to remain implicit (e.g., Gamble, Lee, Howard, & Howard, 2014; Howard Jr & Howard, 1997; Kaufman et al., 2010; Kóbor et al., 2021) and may be less influenced by working memory demands related to explicit search (Janacek & Nemeth, 2013, 2014; Martini et al., 2015). As discussed above, we used the classical SRTT *because* we wanted to allow participants the opportunity to obtain explicit awareness. That is, our primary questions of interest concerned what factors predict how quickly and accurately participants become aware of the pattern in the SRTT (e.g., Do participants form intuitions before developing explicit knowledge? Do better/faster sequence learners report intuitions earlier?). Given evidence provided by the present study that intuitions precede – and predict the quality of – explicit knowledge, subsequent work using the ASRT should focus more specifically on the first part of the pathway: how does implicit learning relate to intuitions (if at all)?

Our findings should also be considered alongside other theoretical frameworks of human cognition. Dual-system accounts indicate that implicit and explicit processes are driven by different inputs and have different functions, but they are nonetheless interlinked in their operation (Evans, 2003; Kahneman, 2003; St. Evans, 2008). According to these perspectives, however, some sort of additional step is needed in order to allow information initially processed in one system to be accessed by the other. For example, the Unexpected Event Hypothesis (Esser & Haider, 2017; Frensch & R nger, 2003; Haider & Frensch, 2005; R nger & Frensch, 2008), drawing in part from error-prediction learning models (Clark, 2013; Rescorla & Wagner, 1972), suggests that explicit knowledge develops from implicit learning when one gains some sort of meta-awareness, often through a consciously-perceivable change in behavior. In the case of the present study, the emergence of an intuition may have functioned in this sort of role; participants intuited block structure (i.e., pattern or random), and then used that intuition to develop more conscious knowledge. In other words, participants gained a meta-awareness of their own intuition, allowing them to explicitly attend to and identify the block structure. It should be noted, however, that none of these explanations necessitate that implicit learning leads directly to intuitions. Rather, intuitions may develop in parallel.

Alternatively, our findings may provide support for single-system accounts of human cognition. According to such perspectives, implicit

and explicit processes are not neurocognitively distinct, but instead belong to a shared, graded system (Cleeremans, 2006; Cleeremans & Jim nez, 2002; Destrebecqz & Cleeremans, 2003; Esser & Haider, 2017). Implicitly-acquired information enters explicit awareness if its representation is strong, stable, and distinct (Cleeremans, 2006). Viewed in the context of the present study, it is likely that the strength, stability, and distinctness of participants' representations increased as they advanced through each learning block. That is, with greater exposure to a specific block's structure, participant were able to obtain more information about its properties (i.e., pattern or random), particularly during the instructed learning phase. When block structure remained implicit (i.e., a participant did not make an accurate self-report), this may have been because the learned information was not distinct, stable, or appropriately integrated with other explicit content, rather than because it had not "moved" from the implicit system to the explicit one. The finding that participants who developed faster intuitions also had better explicit knowledge indicates that participants acquired increasingly more information about structure over the duration of a learning block that, in many cases, culminated in explicit knowledge. It is plausible, though somewhat speculative, that differences in learning rate were also related to the extent to which a representation was explicit, although the finding that learning rate preceding intuitions was unassociated with the accuracy of the intuitions appears contrary to this interpretation.

Results from the present study also extend prior findings concerning the effect of (1) explicit *search* and (2) explicit *knowledge* during the deterministic SRTT. Mixed effects models indicated clear evidence of implicit learning during both the uninstructed and instructed phases of the task. Notably, prior to beginning the instructed (but not uninstructed) learning phase, participants were informed that some blocks may contain complex repeating patterns. They were also asked to indicate when they developed intuitions and explicit knowledge. Prior work has demonstrated that explicit searching – which presumably occurred to a greater degree during the instructed phase – may impede implicit learning by disrupting task elements that would otherwise facilitate learning (for deterministic stimuli; Fletcher et al., 2005; Howard & Howard, 2001; Reber, 2013). Our findings lend additional support for this disruptive effect; implicit learning during the uninstructed phase was significantly greater than implicit learning during the instructed phase. This suggests that the additional top-down processes induced by the instructions to report/search for block structure negatively influenced implicit learning. Although searching may harm performance, having explicit knowledge of the embedded pattern has been shown to amplify RT differences between pattern and random blocks during the deterministic SRTT (Esser & Haider, 2017; Haider et al., 2011; Haider & Rose, 2007). Here, too, our findings support prior work. Mixed effects models indicated a significant 3-way Target Number X Block Condition X Self-Report interaction, with sequence learning (i.e., the difference between pattern and random block RT over time) greater for targets after a self-report. Thus, explicit search may disrupt implicit learning, but once a learner reported more consciously-accessible knowledge (i.e., intuitive or explicit), sequence learning improved. In this way, more accessible knowledge of the embedded sequence may have allowed participants to better anticipate subsequent targets, particularly during pattern blocks. A potential complementary explanation, though not directly reflected by our data, is that, upon indicating knowledge, participants reduced their explicit search (because of a belief that they had identified the block structure). In other words, the improvement in sequence learning could be an indirect consequence of reported knowledge because learners "turned off" their deleterious searching. Future research employing an ASRT-based paradigm, as described above, could provide a worthwhile comparison for these results because divided attention (e.g., searching) has been shown to have no influence on probabilistic sequence learning (Horv th et al., 2020).

Recent initiatives in psychology have re-emphasized the inherent value of introspection and self-report (Locke, 2009), and such approaches have been previously used within the context of the SRTT

(Esser & Haider, 2018; Haider et al., 2011), although in a different manner than in the present study. We see no reason to doubt the validity of the self-report provided by participants. More materially, a number of our findings indicate that participants were able to accurately assess their own knowledge. First, the accuracy of both intuition and explicit knowledge self-reports were significantly greater than chance. Additionally, the observed effect of the self-report on sequence learning (i.e., greater RT differences for pattern and random blocks following self-report) further suggests that participants made a self-report only once they obtained more accessible knowledge. Indeed, failure to observe this effect would have been inconsistent with prior work on the benefits of awareness during the SRTT (Esser & Haider, 2017; Haider et al., 2011; Haider & Rose, 2007).

A limitation of the present study on the implementation level is that data were obtained online. The validity of online data has become a topic of increasing priority in psychology research (Allahbakhsh et al., 2013; Buhrmester, Kwang, & Gosling, 2016; Palan & Schitter, 2018; Smith, Roster, Golden, & Alba, 2016). Although some recent findings suggest superior data from in-person samples (Chmielewski & Kucker, 2020), differences can be mitigated with careful quality control and attention checks that screen out inattentive participants (as was done in the present study; Allahbakhsh et al., 2013; Chmielewski & Kucker, 2020; Thomas & Clifford, 2017). It is perhaps notable that analyses in the present study examined millisecond-level RT information, and that improper participant responding may have been difficult to identify at this level of precision (e.g., as opposed to inappropriate answers to a survey), although there is precedent for examining millisecond-level differences in sequence learning with online samples (e.g., Kahn et al., 2018; Karuza et al., 2019). Moreover, internet and computer speeds vary widely across participants, and these factors may influence things like loading speed and latency (although this is likely to vary primarily between – rather than within – participants). In addition to extensive data quality control, mixed effects models also considered putative differences in computer speed by controlling for how quickly targets appeared on screen for each participant (“Lag time”; see SI). Replicating the present findings using an in-person sample would further demonstrate the reliability of RT data collected online.

To conclude, the present study tested theoretical accounts of the emergence of intuitions from implicit learning using a modified SRTT paradigm. Findings indicated that intuitions were preceded by implicit learning. Although we did not identify an association between implicit learning and intuition accuracy, we found that accuracy and timing of intuitions were correlated with later-reported explicit knowledge. Together, these results suggest that, when individuals gain explicit awareness of implicitly-learned information, the quality of such awareness is related to the quality of the preceding intuitions. Future efforts should be made to investigate whether individual differences in implicit learning are responsible for subsequent variability in intuition accuracy.

## Data availability

Data, code, and preregistration supporting the manuscript are publicly available on the Open Science Framework at: <https://osf.io/4pjmz>.

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## Declaration of Competing Interest

The authors declare no competing interests

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.cognition.2021.105008>.

## References

- Allahbakhsh, M., Benattallah, B., Ignjatovic, A., Motahari-Nezhad, H. R., Bertino, E., & Dustdar, S. (2013). Quality control in crowdsourcing systems: Issues and directions. *IEEE Internet Computing*, 17(2), 76–81.
- Anwyl-Irvine, A. L., Massonnié, J., Flitton, A., Kirkham, N., & Evershed, J. K. (2019). Gorilla in our midst: An online behavioral experiment builder. *Behavior Research Methods*, 1–20.
- Aru, J., & Bachmann, T. (2017). In and out of consciousness: How does conscious processing (D)evolve over time? *Frontiers in Psychology*, 8. <https://doi.org/10.3389/fpsyg.2017.00128>
- Aslin, R. N., & Newport, E. L. (2012). Statistical learning: From acquiring specific items to forming general rules. *Current Directions in Psychological Science*, 21(3), 170–176. <https://doi.org/10.1177/0963721412436806>
- Batterink, L. J., Reber, P. J., & Paller, K. A. (2015). Functional differences between statistical learning with and without explicit training. *Learning & Memory*, 22(11), 544–556.
- Block, N. (1995). On a confusion about a function of consciousness. *Behavioral and Brain Sciences*, 18(2), 227–247.
- Bo, J., Borza, V., & Seidler, R. D. (2009). Age-related declines in visuospatial working memory correlate with deficits in explicit motor sequence learning. *Journal of Neurophysiology*, 102(5), 2744–2754. <https://doi.org/10.1152/jn.00393.2009>
- Bo, J., Jennett, S., & Seidler, R. D. (2012). Differential working memory correlates for implicit sequence performance in young and older adults. *Experimental Brain Research*, 221(4), 467–477. <https://doi.org/10.1007/s00221-012-3189-2>
- Bowers, K. S., Regehr, G., Balthazard, C., & Parker, K. (1990). Intuition in the context of discovery. *Cognitive Psychology*, 22(1), 72–110.
- Buhrmester, M., Kwang, T., & Gosling, S. D. (2016). Amazon's mechanical Turk: A new source of inexpensive, yet high-quality data?.
- Chmielewski, M., & Kucker, S. C. (2020). An MTurk crisis? Shifts in data quality and the impact on study results. *Social Psychological and Personality Science*, 11(4), 464–473. <https://doi.org/10.1177/1948550619875149>
- Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, 36(3), 181–204.
- Cleeremans, A. (2006). *Conscious and unconscious cognition: A graded, dynamic perspective*.
- Cleeremans, A., & Jiménez, L. (2002). Implicit learning and consciousness: A graded, dynamic perspective. *Implicit Learning and Consciousness*, 1–40.
- Destrebecqz, A., & Cleeremans, A. (2001). Can sequence learning be implicit? New evidence with the process dissociation procedure. *Psychonomic Bulletin & Review*, 8(2), 343–350.
- Destrebecqz, A., & Cleeremans, A. (2003). Temporal effects in sequence learning. *Advances in Consciousness Research*, 48, 181–214.
- Dienes, Z., & Perner, J. (1999). A theory of implicit and explicit knowledge. *Behavioral and Brain Sciences*, 22(5), 735–808. <https://doi.org/10.1017/S0140525X99002186>
- Ellis, N. C. (1994). Implicit and explicit language learning. *Implicit and Explicit Learning of Languages*, 79–114.
- Ellis, R. (2009). Implicit and explicit learning, knowledge and instruction. *Implicit and Explicit Knowledge in Second Language Learning, Testing and Teaching*, 42, 3–25.
- Epstein, S. (2010). Demystifying intuition: What it is, what it does, and how it does it. *Psychological Inquiry*, 21(4), 295–312. <https://doi.org/10.1080/1047840X.2010.523875>
- Esser, S., & Haider, H. (2017). The emergence of explicit knowledge in a serial reaction time task: The role of experienced fluency and strength of representation. *Frontiers in Psychology*, 8. <https://doi.org/10.3389/fpsyg.2017.00502>
- Esser, S., & Haider, H. (2018). Action-effects enhance explicit sequential learning. *Psychological Research*, 82(6), 1113–1129. <https://doi.org/10.1007/s00426-017-0883-5>
- Evans, J. S. B. (2003). In two minds: Dual-process accounts of reasoning. *Trends in Cognitive Sciences*, 7(10), 454–459.
- Fletcher, P. C., Zafiris, O., Frith, C. D., Honey, R. A. E., Corlett, P. R., Zilles, K., & Fink, G. R. (2005). On the benefits of not trying: Brain activity and connectivity reflecting the interactions of explicit and implicit sequence learning. *Cerebral Cortex*, 15(7), 1002–1015. <https://doi.org/10.1093/cercor/bbh201>
- Frensch, P. A., & Rüniger, D. (2003). Implicit learning. *Current Directions in Psychological Science*, 12(1), 6.
- Fu, Q., Dienes, Z., & Fu, X. (2010a). Can unconscious knowledge allow control in sequence learning? *Consciousness and Cognition*, 19(1), 462–474. <https://doi.org/10.1016/j.concog.2009.10.001>
- Fu, Q., Dienes, Z., & Fu, X. (2010b). The distinction between intuition and guessing in the SRT task generation: A reply to Norman and Price. *Consciousness and Cognition*, 19(1), 478–480. <https://doi.org/10.1016/j.concog.2009.12.006>

- Gabrieli, J. D. E. (1998). Cognitive neuroscience of human memory. *Annual Review of Psychology*, 49(1), 87–115. <https://doi.org/10.1146/annurev.psych.49.1.87>
- Gamble, K. R., Lee, J. M., Howard, J. H., & Howard, D. V. (2014). Effects of priming goal pursuit on implicit sequence learning. *Experimental Brain Research*, 232(11), 3635–3643. <https://doi.org/10.1007/s00221-014-0454-2>
- Goldstein, H. (2011). *Multilevel statistical models* (Vol. 922). John Wiley & Sons.
- Grahn, J. A., & Rowe, J. B. (2013). Finding and feeling the musical beat: Striatal dissociations between detection and prediction of regularity. *Cerebral Cortex*, 23(4), 913–921. <https://doi.org/10.1093/cercor/bhs083>
- Greenwald, A. G., Banaji, M. R., Rudman, L. A., Farnham, S. D., Nosek, B. A., & Mellott, D. S. (2002). A unified theory of implicit attitudes, stereotypes, self-esteem, and self-concept. *Psychological Review*, 109(1), 3.
- Haider, H., Eichler, A., & Lange, T. (2011). An old problem: How can we distinguish between conscious and unconscious knowledge acquired in an implicit learning task? *Consciousness and Cognition*, 20(3), 658–672. <https://doi.org/10.1016/j.concog.2010.10.021>
- Haider, H., & Frensch, P. A. (2005). The generation of conscious awareness in an incidental learning situation. *Psychological Research*, 69(5–6), 399–411.
- Haider, H., & Rose, M. (2007). How to investigate insight: A proposal. *Methods*, 42(1), 49–57. <https://doi.org/10.1016/j.ymeth.2006.12.004>
- Hodgkinson, G. P., Langan-Fox, J., & Sadler-Smith, E. (2008). Intuition: A fundamental bridging construct in the behavioural sciences. *British Journal of Psychology*, 99(1), 1–27. <https://doi.org/10.1348/000712607X216666>
- Horváth, K., Török, C., Pesthy, O., Nemeth, D., & Janacek, K. (2020). Divided attention does not affect the acquisition and consolidation of probabilistic probabilities. *Scientific Reports*, 10(1), 22450. <https://doi.org/10.1038/s41598-020-79232-y>
- Howard, D. V., & Howard, J. H. (2001). When it does hurt to try: Adult age differences in the effects of instructions on implicit pattern learning. *Psychonomic Bulletin & Review*, 8(4), 798–805.
- Howard, J. H., Jr., & Howard, D. V. (1997). Age differences in implicit learning of higher order dependencies in serial patterns. *Psychology and Aging*, 12(4), 634.
- Huang, J., Li, Y., Zhang, J., Wang, X., Huang, C., Chen, A., & Liu, D. (2017). fMRI investigation on gradual change of awareness states in implicit sequence learning. *Scientific Reports*, 7(1), 16731. <https://doi.org/10.1038/s41598-017-16340-2>
- Janacek, K., & Nemeth, D. (2013). Implicit sequence learning and working memory: Correlated or complicated? *Cortex*, 49(8), 2001–2006. <https://doi.org/10.1016/j.cortex.2013.02.012>
- Janacek, K., & Nemeth, D. (2014). The puzzle is complicated: When should working memory be related to implicit sequence learning, and when should it not? (response to Martini et al.). *Cortex: A Journal Devoted to the Study of the Nervous System and Behavior*, 64, 411–412.
- Kahn, A. E., Karuza, E. A., Vettel, J. M., & Bassett, D. S. (2018). Network constraints on learnability of probabilistic motor sequences. *Nature Human Behaviour*, 2(12), 936–947. <https://doi.org/10.1038/s41562-018-0463-8>
- Kahneman, D. (2003). A perspective on judgment and choice: Mapping bounded rationality. *American Psychologist*, 58(9), 697–720. <https://doi.org/10.1037/0003-066X.58.9.697>
- Kalra, P. B., Gabrieli, J. D., & Finn, A. S. (2019). Evidence of stable individual differences in implicit learning. *Cognition*, 190, 199–211.
- Karuza, E. A., Kahn, A. E., & Bassett, D. S. (2019). Human sensitivity to community structure is robust to topological variation. *Complexity*, 2019.
- Kaufman, S. B., DeYoung, C. G., Gray, J. R., Jiménez, L., Brown, J., & Mackintosh, N. (2010). Implicit learning as an ability. *Cognition*, 116(3), 321–340. <https://doi.org/10.1016/j.cognition.2010.05.011>
- Kóbor, A., Kardos, Z., Horváth, K., Janacek, K., Takács, Á., Csépe, V., & Nemeth, D. (2021). Implicit anticipation of probabilistic regularities: Larger CNV emerges for unpredictable events. *Neuropsychologia*, 156, Article 107826. <https://doi.org/10.1016/j.neuropsychologia.2021.107826>
- Krumhansl, C. L., & Keil, F. C. (1982). Acquisition of the hierarchy of tonal functions in music. *Memory & Cognition*, 10(3), 243–251. <https://doi.org/10.3758/BF03197636>
- Krumhansl, C. L., Louhivuori, J., Toivainen, P., Järvinen, T., & Eerola, T. (1999). Melodic expectation in Finnish spiritual folk hymns: Convergence of statistical, behavioral, and computational approaches. *Music Perception: An Interdisciplinary Journal*, 17(2), 151–195. <https://doi.org/10.2307/40285890>
- Lieberman, M. D. (2000). Intuition: A social cognitive neuroscience approach. *Psychological Bulletin*, 126(1), 109–137. <https://doi.org/10.1037/0033-2909.126.1.109>
- Locke, E. A. (2009). It's time we brought introspection out of the closet. *Perspectives on Psychological Science*, 4(1), 24–25. <https://doi.org/10.1111/j.1745-6924.2009.01090.x>
- Longford, N. T. (1995). Random coefficient models. In *Handbook of statistical modeling for the social and behavioral sciences* (pp. 519–570). Springer.
- Love, J., Selker, R., Marsman, M., Jamil, T., Dropmann, D., Verhagen, J., ... Epskamp, S. (2019). JASP: Graphical statistical software for common statistical designs. *Journal of Statistical Software*, 88(1), 1–17.
- Martini, M., Sachse, P., Furtner, M. R., & Gaschler, R. (2015). Why should working memory be related to incidentally learned sequence structures? *Cortex*, 64, 407–410. <https://doi.org/10.1016/j.cortex.2014.05.016>
- Miyawaki, K. (2012). Selective learning enabled by intention to learn in sequence learning. *Psychological Research*, 76(1), 84–96. <https://doi.org/10.1007/s00426-011-0325-8>
- Nemeth, D., Janacek, K., Csifcsak, G., Szvoboda, G., Jr., & J. H. H., & Howard, D. V.. (2011). Interference between sentence processing and probabilistic implicit sequence learning. *PLoS One*, 6(3), Article e17577. <https://doi.org/10.1371/journal.pone.0017577>
- Nissen, M. J., & Bullemer, P. (1987). Attentional requirements of learning: Evidence from performance measures. *Cognitive Psychology*, 19(1), 1–32.
- Norman, E., & Price, M. C. (2010). Measuring “intuition” in the SRT generation task. *Consciousness and Cognition*, 19(1), 475–477. <https://doi.org/10.1016/j.concog.2009.11.004>
- Overgaard, M. (2018). Phenomenal consciousness and cognitive access. *Philosophical Transactions of the Royal Society, B: Biological Sciences*, 373(1755), 20170353. <https://doi.org/10.1098/rstb.2017.0353>
- Palan, S., & Schitter, C. (2018). Prolific.ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, 17, 22–27. <https://doi.org/10.1016/j.jbef.2017.12.004>
- Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, 70, 153–163. <https://doi.org/10.1016/j.jesp.2017.01.006>
- Reber, A. S. (1989). Implicit learning and tacit knowledge. *Journal of Experimental Psychology: General*, 118(3), 219.
- Reber, A. S. (1992). The cognitive unconscious: An evolutionary perspective. *Consciousness and Cognition*, 1(2), 93–133.
- Reber, P. J. (2013). The neural basis of implicit learning and memory: A review of neuropsychological and neuroimaging research. *Neuropsychologia*, 51(10), 2026–2042.
- Rescorla, R. A., & Wagner, A. R. (1972). A theory of Pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. *Classical Conditioning II: Current Research and Theory*, 2, 64–99.
- Robertson, E. M. (2007). The serial reaction time task: Implicit motor skill learning? *Journal of Neuroscience*, 27(38), 10073–10075. <https://doi.org/10.1523/JNEUROSCI.2747-07.2007>
- Robinson, P. (1997). Individual differences and the fundamental similarity of implicit and explicit adult second language learning. *Language Learning*, 47(1), 45–99. <https://doi.org/10.1111/0023-8333.21997002>
- Rohrmeier, M., & Widdess, R. (2017). Incidental learning of melodic structure of north Indian music. *Cognitive Science*, 41(5), 1299–1327.
- Rose, M., Haider, H., & Buchel, C. (2010). The emergence of explicit memory during learning. *Cerebral Cortex*, 20(12), 2787–2797. <https://doi.org/10.1093/cercor/bhq025>
- Rosenthal, C. R., Andrews, S. K., Antoniadis, C. A., Kennard, C., & Soto, D. (2016). Learning and recognition of a non-conscious sequence of events in human primary visual cortex. *Current Biology*, 26(6), 834–841. <https://doi.org/10.1016/j.cub.2016.01.040>
- Rünger, D., & Frensch, P. A. (2008). How incidental sequence learning creates reportable knowledge: The role of unexpected events. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 34(5), 1011–1026. <https://doi.org/10.1037/a0012942>
- Rüsseler, J., Münte, T. F., & Wiswede, D. (2018). On the influence of informational content and key-response effect mapping on implicit learning and error monitoring in the serial reaction time (SRT) task. *Experimental Brain Research*, 236(1), 259–273. <https://doi.org/10.1007/s00221-017-5124-z>
- Saffran, J. R., Aslin, R. N., & Newport, E. L. (1996). Statistical learning by 8-month-old infants. *Science*, 274(5294), 1926–1928. <https://doi.org/10.1126/science.274.5294.1926>
- Sandberg, K., Timmermans, B., Overgaard, M., & Cleeremans, A. (2010). Measuring consciousness: Is one measure better than the other? *Consciousness and Cognition*, 19(4), 1069–1078.
- Sergent, C. (2018). The offline stream of conscious representations. *Philosophical Transactions of the Royal Society, B: Biological Sciences*, 373(1755), 20170349. <https://doi.org/10.1098/rstb.2017.0349>
- Seth, A. K., Dienes, Z., Cleeremans, A., Overgaard, M., & Pessoa, L. (2008). Measuring consciousness: Relating behavioural and neurophysiological approaches. *Trends in Cognitive Sciences*, 12(8), 314–321.
- Shanks, D. R. (2005). Implicit learning. In *Handbook of Cognition* (pp. 202–220).
- Shirley, D. A., & Langan-Fox, J. (1996). Intuition: A review of the literature. *Psychological Reports*, 79(2), 563–584.
- Smith, S. M., Roster, C. A., Golden, L. L., & Alba, G. S. (2016). A multi-group analysis of online survey respondent data quality: Comparing a regular USA consumer panel to MTurk samples. *Journal of Business Research*, 69(8), 3139–3148.
- Song, S., Howard, J. H., & Howard, D. V. (2007). Implicit probabilistic sequence learning is independent of explicit awareness. *Learning & Memory*, 14(3), 167–176.
- Song, S., Howard, J. H., & Howard, D. V. (2008). Perceptual sequence learning in a serial reaction time task. *Experimental Brain Research*, 189(2), 145–158. <https://doi.org/10.1007/s00221-008-1411-z>
- Song, S., Marks, B., Howard, J. H., Jr., & Howard, D. V. (2009). Evidence for parallel explicit and implicit sequence learning systems in older adults. *Behavioural Brain Research*, 196(2), 328–332.
- St. Evans, J. B. T. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annual Review of Psychology*, 59(1), 255–278. <https://doi.org/10.1146/annurev.psych.59.1.255>
- Stanovich, K. E., & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate? *Behavioral and Brain Sciences*, 23(5), 645–665.
- Stata, S. (2017). *Stata statistical software: Release 15*. College Station, TX: StataCorp LLC, Free Trial.
- Sun, R., Merrill, E., & Peterson, T. (2001). From implicit skills to explicit knowledge: A bottom-up model of skill learning. *Cognitive Science*, 25(2), 203–244.
- Sun, R., Slusarz, P., & Terry, C. (2005). The interaction of the explicit and the implicit in skill learning: A dual-process approach. *Psychological Review*, 112(1), 159–192. <https://doi.org/10.1037/0033-295X.112.1.159>

- Sun, R., & Zhang, X. (2004). Top-down versus bottom-up learning in cognitive skill acquisition. *Cognitive Systems Research*, 5(1), 63–89. <https://doi.org/10.1016/j.cogsys.2003.07.001>
- Thomas, K. A., & Clifford, S. (2017). Validity and Mechanical Turk: An assessment of exclusion methods and interactive experiments. *Computers in Human Behavior*, 77, 184–197. <https://doi.org/10.1016/j.chb.2017.08.038>
- Vadillo, M. A., Konstantinidis, E., & Shanks, D. R. (2016). Underpowered samples, false negatives, and unconscious learning. *Psychonomic Bulletin & Review*, 23(1), 87–102. <https://doi.org/10.3758/s13423-015-0892-6>
- Verleger, R., Seitz, A., Yordanova, J., & Kolev, V. (2015). Is insight a godsend? Explicit knowledge in the serial response-time task has precursors in EEG potentials already at task onset. *Neurobiology of Learning and Memory*, 125, 24–35. <https://doi.org/10.1016/j.nlm.2015.07.012>
- Weinberger, A. B., Gallagher, N. M., Warren, Z. J., English, G. A., Moghaddam, F. M., & Green, A. E. (2020). Implicit pattern learning predicts individual differences in belief in god in the United States and Afghanistan. *Nature Communications*, 11(1), 1–12. <https://doi.org/10.1038/s41467-020-18362-3>
- Wessel, J. R., Haider, H., & Rose, M. (2012). The transition from implicit to explicit representations in incidental learning situations: More evidence from high-frequency EEG coupling. *Experimental Brain Research*, 217(1), 153–162. <https://doi.org/10.1007/s00221-011-2982-7>
- Willingham, D. B. (1999). Implicit motor sequence learning is not purely perceptual. *Memory & Cognition*, 27(3), 561–572.
- Willingham, D. B. (2001). Becoming aware of motor skill. *Trends in Cognitive Sciences*, 5(5), 181–182.
- Willingham, D. B., & Dumas, J. A. (1997). Long-term retention of a motor skill: Implicit sequence knowledge is not retained after a one-year delay. *Psychological Research*, 60(1), 113–119.
- Willingham, D. B., & Goedert-Eschmann, K. (1999). The relation between implicit and explicit learning: Evidence for parallel development. *Psychological Science*, 10(6), 531–534.
- Willingham, D. B., Salidis, J., & Gabrieli, J. D. E. (2002). Direct comparison of neural systems mediating conscious and unconscious skill learning. *Journal of Neurophysiology*, 88(3), 1451–1460. <https://doi.org/10.1152/jn.2002.88.3.1451>
- Yordanova, J., Kirov, R., & Kolev, V. (2015). Increased performance variability as a marker of implicit/explicit interactions in knowledge awareness. *Frontiers in Psychology*, 6. <https://doi.org/10.3389/fpsyg.2015.01957>
- Yordanova, J., Kolev, V., Verleger, R., Bataghva, Z., Born, J., & Wagner, U. (2008). Shifting from implicit to explicit knowledge: Different roles of early- and late-night sleep. *Learning & Memory*, 15(7), 508–515. <https://doi.org/10.1101/lm.897908>