

# Intact implicit learning in autism spectrum conditions

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Individuals with autism spectrum condition (ASC) have diagnostic impairments in skills that are associated with an implicit acquisition; however, it is not clear whether ASC individuals show specific implicit learning deficits. We compared ASC and typically developing (TD) individuals matched for IQ on five learning tasks: four implicit learning tasks—contextual cueing, serial reaction time, artificial grammar learning, and probabilistic classification learning tasks—that used procedures expressly designed to minimize the use of explicit strategies, and one comparison explicit learning task, paired associates learning. We found implicit learning to be intact in ASC. Beyond no evidence of differences, there was evidence of statistical equivalence between the groups on all the implicit learning tasks. This was not a consequence of compensation by explicit learning ability or IQ. Furthermore, there was no evidence to relate implicit learning to ASC symptomatology. We conclude that implicit mechanisms are preserved in ASC and propose that it is disruption by other atypical processes that impact negatively on the development of skills associated with an implicit acquisition.

*Keywords:* Implicit learning; Autism; Explicit learning.

Autism spectrum conditions (ASC) are characterized by social, communicative, and motor impairments (*Diagnostic and Statistical Manual of Mental Disorders—Fourth Edition, DSM-IV*; American Psychiatric Association, 1994). Implicit learning

is thought to be one important mechanism for acquiring social, communicative, and motor skills (e.g., Kaufman et al., 2009; Meltzoff, Kuhl, Movellan, & Sejnowski, 2009; Perruchet, 2008), raising the possibility that social, communicative,

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and motor impairments in ASC may arise, in part, from a general deficit in implicit learning (L. G. Klinger, Klinger, & Pohlig, 2007; Mostofsky, Goldberg, Landa, & Denckla, 2000; Romero-Munigua, 2008).

Implicit learning is popularly characterized as learning that takes place without awareness (A. S. Reber, 1967), although such an extreme conception has always been controversial (e.g., Shanks, 2005). There is better evidence and consensus for defining implicit learning as the learning that proceeds from *practice with any structured environment*, in the absence of an intention to learn, and results in knowledge that improves performance even when it is difficult to verbalize (for discussion see Perruchet, 2008; Shanks, 2005).

Testing the hypothesis that such implicit learning is impaired in ASC requires a comparison of the performance of individuals with and without ASC on tasks taken to evidence implicit learning. The approach is not without precedence; the performance of several clinical populations on various implicit and explicit learning tasks has been examined (Keri, 2003). These include amnesia (e.g., Chun & Phelps, 1999); Parkinson's disease (e.g., P. J. Reber & Squire, 1999); Huntington's disease (e.g., Knowlton, Squire, Paulsen, Swerdlow, & Swenson, 1996); Williams syndrome and Down syndrome (e.g., Vicari, Verucci, & Carlesimo, 2007); obsessive-compulsive disorder (OCD; Rauch et al., 2007); Alzheimer's disease (e.g., Eldridge, Masterman, & Knowlton, 2002); dyslexia (e.g., Folia et al., 2008); Tourette's syndrome (Kéri, Szlobodnyik, Benedek, Janka, & Gáboros, 2002); schizophrenia (e.g., Siegert, Weatherall, & Bell, 2008); psychosis and attention-deficit/hyperactivity disorder (ADHD; Karatekin, White, & Bingham, 2009); and intellectual disability (Vinter & Detable, 2003). Most pertinently to the current study, existing empirical research has explored implicit learning patterns in ASC (Gordon & Stark, 2007; L. G. Klinger & Dawson, 2001; L. G. Klinger et al., 2007; Mostofsky et al., 2000).

Several studies have claimed to find impairments in implicit learning in ASC, on a range of different implicit learning tasks. For example,

Mostofsky et al., (2000) and Gordon and Stark (2007) reported that individuals with ASC performed worse than typically developing (TD) individuals on an implicit learning procedure, the serial reaction time task (SRT; Nissen & Bullemer, 1987). In the typical SRT procedure, participants are instructed to respond as quickly and accurately as possible to the location of a stimulus that is presented at one of several different possible locations from one trial to the next. Unknown to the participants, the locations in which the stimuli appear follow a regular sequence, and participants typically become faster to respond to locations predicted by the sequence. Learning is implicit because participants are unable to verbalize easily the details of the sequence, with only fragmentary knowledge present, which is unable to account for performance (Jiménez, Mendez, & Cleeremans, 1996; Jiménez, Vaquero, & Lupiáñez, 2006).

However, there is some reason to question whether the procedure used by Gordon and Stark (2007) and Mostofsky et al. (2000) adequately assessed implicit learning. Subsequent research has shown that procedures involving slowly repeating, so-called "deterministic sequences" (i.e., sequences that follow a continually and slowly repeating sequence without interruption) are more likely to encourage the development and use of explicit strategies to solve the task (e.g., Destrebecqz & Cleeremans, 2001, 2003; Jiménez et al., 1996; Norman, Price, Duff, & Mentzoni, 2007; Schvaneveldt & Gomez, 1998). Since Gordon and Stark (2007) and Mostofsky et al. (2000) used slowly repeating deterministic sequences (the response-to-stimulus interval was 500 ms and 1,500 ms, respectively), it is therefore hard to disentangle to what extent the reported differences in performance between the two groups are due to differences in implicit or explicit learning.

Furthermore, neither of these studies completely matched the two participating groups for IQ. The issue of IQ is highly important: While implicit learning performance has been shown to be unrelated to IQ, explicit learning is strongly correlated (e.g., Gebauer & Mackintosh, 2007, 2009; Kaufman et al., 2009; A. S. Reber, Walkenfeld,

& Hernstadt, 1991). Therefore, if the task procedures encouraged explicit learning, given the ASC-group had lower IQs, the ASC-deficit would be expected and more likely attributable to explicit processes. This interpretation seems particularly feasible given that when researchers (Barnes et al., 2008) compared an ASC group with a TD group well matched for IQ and used a more complicated sequence with shorter response-to-stimulus intervals, then the conclusion was that sequence learning is intact in ASC individuals. In this study, Barnes et al. also found no evidence for differences between the groups on a contextual cueing (CC) task (Chun & Jiang, 1998). CC is a visual search task in which participants are shown displays of stimuli and are required to detect a target stimulus (e.g., a rotated *T*) within a subset of distractor stimuli (e.g., rotated *L*s). On half of all the displays, the arrangement of the distractors is highly predictive of the location of the target. Participants are typically faster to respond on these trials than on trials in which displays do not reliably predict the location of the target. Learning is implicit because when participants are given a test of their explicit knowledge—for example, having to recognize the predictive contexts (Chun & Jiang, 1998), or to generate the location of the missing target when presented with predictive displays in which the target has been replaced by another distractor (Chun & Jiang, 2003; Jiménez & Vázquez, 2009)—then participants perform no better than chance.

There is also discrepancy between the findings of studies assessing the performance of individuals with ASC on another classic implicit learning procedure, artificial grammar learning (AGL: A. S. Reber, 1967). In the standard AGL procedure, participants are exposed to a series of letter strings, which have been created according to an artificial grammar. However, only once this initial exposure is finished are participants told about the rules. Further, they are then instructed that they will see some new strings and will have to decide whether or not strings conform to the rules. Usually, participants are able to make these decisions with better-than-chance accuracy but

have little ability to describe the rules (for a recent review, see Pothos, 2007). Whilst one study claimed to find ASC deficits (L. G. Klinger et al., 2007), another found that individuals with ASC did no worse than controls on the task (reported in L. G. Klinger et al., 2007; L. G. Klinger, Lee, Bush, Klinger, & Crump, 2001, as cited in L. G. Klinger et al., 2007). It should be noted, however, that the tasks used in these studies were adapted versions of the classic AGL test (e.g., the tasks used shape rather than letter stimuli and for the test phase required a two-alternative forced-choice discrimination rather than a single-stimulus classification decision) raising the possibility that the adaptations allowed the use of explicit strategies to learn the task rather than proving stringent assessments of implicit processes. This interpretation was corroborated by the observation of a correlation of AGL performance with IQ (L. G. Klinger et al., 2007; L. G. Klinger et al., 2001, as cited in L. G. Klinger et al., 2007). The difference in outcome of each study may therefore be due to differences between the groups of children with ASC in each study to use explicit strategies successfully. One reason to suppose this is that although the groups were well matched for mental age in the study in which deficits were found (L. G. Klinger et al., 2007), they differed on chronological age and IQ. Thus, if tasks used in studies of implicit learning in ASC lend themselves to explicit, IQ-related strategies, it will be difficult to dissociate any performance deficit due to differences in a capacity to learn implicitly from differences in the IQ-mediated explicit contribution.

Attempts have also been made to assess implicit learning on category learning tasks, and some studies have claimed to show a deficit (e.g., L. G. Klinger & Dawson, 2001; L. G. Klinger et al., 2007). However, all such studies used a deterministic, as opposed to a probabilistic, category learning task, which would be more likely to encourage the use of explicit strategies (L. G. Klinger & Dawson, 2001; L. G. Klinger et al., 2007; Molesworth, Bowler, & Hampton, 2005). This interpretation is corroborated by the

correlation of deterministic category learning with IQ in the one study that reported this relationship (L. G. Klinger et al., 2007). Further, although both the studies demonstrating a deficit matched the ASC and TD groups for verbal mental age, neither study matched the groups for IQ or chronological age (L. G. Klinger & Dawson, 2001; L. G. Klinger et al., 2007). In another study (Molesworth et al., 2005) that did match for chronological age, mental age, and IQ, the deficit was not replicated: ASC performance was found to be intact. Thus, it is not clear that there are ASC differences in performance on nonprobabilistic category learning tasks. Even if differences are established on this version of the task, it seems likely that they could be due to differences in cognitive processes other than implicit learning.

This review suggests that although there may be a deficit in implicit learning in ASC, it is possible that performance deficits observed so far may arise as a consequence of the recruitment of other, particularly explicit, cognitive processes. This is especially important given that the studies reporting an ASC-deficit did not stringently match ASC and control groups for IQ, and explicit, in contrast to implicit, processes correlate strongly with IQ. Furthermore, it is known that the use of explicit strategies usually changes performance on implicit learning procedures (e.g., Gebauer & Mackintosh, 2007) and that differences between diagnostic groups on an ostensibly implicit task can be attributable to differences in the explicit rather than the implicit component of the task (Koenig et al., 2008). Therefore, in order to better identify whether such differences rely on either explicit or implicit learning processes, implicit learning procedures are needed that have not been specifically adapted for use with ASC children and thus avoid the use of explicit strategies. On such procedures, it is well established that the underlying complexity of the information to be learned makes it very difficult for explicit strategies to emerge. The current study uses four such unduplicated procedures (AGL, SRT, CC, and probabilistic classification learning, PCL: Gluck & Bower, 1988). The basic structure of the AGL,

SRT, and CC tasks has been described above. In a typical PCL task, participants have to classify or make decisions about stimuli. Following each decision, the participant receives feedback. However, the feedback is probabilistic, and, therefore, for a given stimulus there is not a definitively right answer; instead each stimulus outcome is associated with a probability greater than zero but less than one. Nonetheless, participants are able to classify stimuli with greater accuracy than chance would predict. Yet, because participants have very little, if any, insight into the relationship between the stimuli and outcomes, the learning is described as implicit (e.g., Gluck, Shohamy, & Myers, 2002).

The reason for using four tests, rather than just a single test as in many of the studies above, is that implicit learning tasks necessitate psychological processes in addition to learning, such as encoding and selective attention, and furthermore different implicit learning tasks make different demands of such processes (e.g., Seger, 1994; Squire, Knowlton, & Musen, 1993). Therefore, in order to control for variations in task demands and to allow conclusions about implicit learning in general, it is critical to compare the performance of the same individuals on a range of implicit learning procedures. To illustrate the point, Knowlton et al. (1996), Negash et al. (2007a), Negash et al. (2007b), and Howard, Howard, Japikse, and Eden (2006) have all found impairment on one, but not another, implicit learning task between different clinical groups.

We also assessed the two groups on an explicit learning task, paired-associates learning (PAL). We argued above that explicit learning was unintentionally measured in several previous attempts to assess implicit learning and that in groups unmatched for IQ, it was the explicit processes that were responsible for an ASC performance deficit. It is therefore clearly important to include an overtly explicit task to investigate these relationships directly. Also, it has been argued that children with ASC use explicit processes to compensate for deficits in implicit learning (L. G. Klinger et al., 2007). Therefore, in order to properly understand any preservation or deficit

that emerges in implicit learning, it is necessary to have a comparison with performance on an explicit task. While L. G. Klinger et al. (2007) have ostensibly made the comparison, the measures of explicit learning used were actually IQ tests, which do not involve any learning during the course of the experiment.

As discussed, the current literature on implicit learning in ASC highlights different findings between studies. Given this conflict, and in the context of preserved and enhanced abilities in ASC (Mottron, Dawson, Soulières, Hubert, & Burack, 2006), it is also necessary that analyses should properly consider the possibility that implicit learning is preserved in ASC. To this end, the current study employs equivalence analysis (Rogers, Howard, & Vessey, 1993; Stegner, Bostrom, & Greenfield, 1996) to consider all learning data and consequently does not rely on a failure to reject a null hypothesis as a reason to suppose that performance is preserved in ASC.

Finally, it has also been claimed that implicit learning deficits may play a role in the social, language, and motor deficits common to ASC (L. G. Klinger et al., 2007; Mostofsky et al., 2000). In order to establish the truth of this suggestion, it would not be sufficient to evidence group differences on tests of implicit learning. Instead, performance on implicit learning tasks would have to be related to an index of such diagnostic deficits (L. G. Klinger et al., 2007). Therefore, we asked participants' parents to complete the Social Communication Questionnaire (SCQ), which provides a reliable index of autistic symptomatology to relate to implicit learning performance (Rutter, Bailey, Lord, & Berument, 2003).

Our primary aim was to test the hypothesis that individuals with ASC would show performance deficits on a range of implicit learning tasks, which could not be attributed to other factors such as explicit strategies or task demands. In brief, we found no support for this hypothesis; instead we found evidence of equivalence (Rogers et al., 1993; Stegner et al., 1996) between individuals with and without ASC on implicit learning procedures. This was not a

consequence of compensation by explicit learning ability or IQ. Furthermore, there was no evidence to relate implicit learning to an index of ASC symptomatology.

## Method

### *Participants*

A total of 31 children with ASC (referred to as the ASC group) and 31 typically developing children (referred to as the TD group) participated. All children in the ASC group met established criteria for ASC, such as those specified in *DSM-IV* (American Psychiatric Association, 1994) and had previously received a diagnosis for ASC by trained clinicians using instruments such as the Autism Diagnostic Interview (Le Couteur, Lord, & Rutter, 2003). Any other psychiatric diagnosis acted as an exclusion criterion for both the ASC and TD group. The two groups of children were matched for sex (28 male, 3 female) and chronological age,  $t(55) = 0.28$ ,  $p = .78$ ,  $d = 0.07$ , but differed on Verbal IQ,  $t(50) = 1.83$ ,  $p = .07$ ,  $d = 0.47$ , Performance IQ,  $t(52) = 1.83$ ,  $p = .07$ ,  $d = 0.47$ , and Full Scale IQ,  $t(49) = 2.04$ ,  $p = .05$ ,  $d = 0.52$ , of the Wechsler Abbreviated Scale of Intelligence (WASI; Wechsler, 1999; see Table 1). A subgroup from each group of children was selected who were matched for IQ. The subgroups comprised 26 children with ASC and 26 children with TD. These children were matched for sex (24 male, 2 female), chronological age,  $t(50) = 0.88$ ,  $p = .39$ ,  $d = 0.24$ , Verbal IQ,  $t(50) = 0.61$ ,  $p = .55$ ,  $d = 0.17$ , Performance IQ,  $t(45) = 0.51$ ,  $p = .61$ ,  $d = 0.14$ , and Full Scale IQ,  $t(44) = 0.71$ ,  $p = .48$ ,  $d = 0.20$ , of the WASI, and all had IQs within the typical range (the lowest score was 83; see Table 1). The main analyses were conducted on the data from these subgroups. However, a final analysis was conducted using the entire sample, in order to examine the role of IQ in explicit and implicit learning. Table 1 presents the participant characteristics for both the entire groups and the subgroups matched for IQ. Informed parental consent and the assent of the children were obtained, and ethical permission to conduct the study was

**Table 1.** Mean age and WASI IQ scores for the ASC and TD groups

		N	Chronological age			IQ								
						Verbal			Performance			Full scale		
			M	SD	Range	M	SD	Range	M	SD	Range	M	SD	Range
Entire sample	TD	31	11.7	1.5	8.9–14.3	106.9	11.6	81–127	107.0	12.3	81–135	107.8	11.5	88–135
	ASC	31	11.6	1.1	8.7–14.4	99.7	18.5	65–147	99.5	18.9	62–136	99.6	19.2	66–147
IQ-matched subgroups	TD	26	11.8	1.6	8.9–14.3	104.3	10.5	81–122	104.1	10.9	81–127	104.7	9.4	88–122
	ASC	26	11.5	1.2	8.7–14.4	102.2	13.5	76–122	102.2	15.7	74–132	102.4	14.1	83–126

*Note:* Mean age in years. WASI = Wechsler Abbreviated Scale of Intelligence. ASC = autism spectrum condition. TD = typically developing.

received from the Cambridge Psychology Research Ethics Committee. A total of 18 of the parents of children with ASC (15 of the ASC-subgroup) and 23 of the parents of TD children (19 of the TD-subgroup) completed the SCQ (Rutter et al., 2003). The SCQ is a screening tool for autism, which comprises 40 items derived from the Autism Diagnostic Interview–Revised (ADI-R). The raw scores on the SCQ were converted into percentage scores. All the children in the TD group had scores below the cut-off score of 38.46% specified by Rutter et al.,  $M = 10.43\%$ ,  $SD = 7.14\%$ , range = 2.56–33.33%; for the TD-subgroup,  $M = 10.87\%$ ,  $SD = 7.71\%$ , range = 2.56 – 33.33%. Further, the highest score for the TD group was 5.49 standard deviations (5.11 SDs for the subgroup) below the mean of the ASC group,  $M = 72.59\%$ ,  $SD = 15.82\%$ , range = 30.77–92.31%; for the ASC-subgroup,  $M = 72.75\%$ ,  $SD = 17.24\%$ , range = 30.77–92.31%.

### Apparatus

A 14-inch LCD notebook computer was used for all computerized testing. For the SRT and CC tasks, timing accuracy was of the utmost importance, and therefore these tasks were presented using DMDX software, and participants recorded their responses using a four-button PIO12 response box (Forster & Forster, 2003). Other tasks were presented using: SuperLabPro for the AGL Task; RealBasic for the PCL; and Inquisit

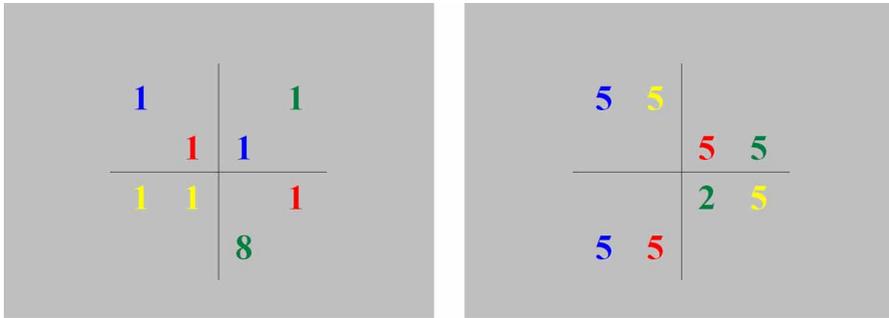
for the PAL. For all these tasks, responses were recorded using the notebook's keyboard.

### Tasks and procedure

#### Implicit learning tasks

**Contextual cueing (CC) task.** A continuous version of the CC task was used, in which successive trials followed each other with minimal delay (50 ms) and were not preceded by a fixation point. Jiménez and Vázquez (2009) have shown that this procedure results in levels of learning similar to the usual discrete version developed by Chun and Jiang (1998). In addition, Jiménez and Vázquez's (2009) procedure was followed by using four different responses instead of the usual two-alternative task. This procedure was chosen to make the motor requirements of this task more comparable to those required by the SRT task (see below). Therefore, should specific deficits emerge, they can be more confidently attributed to differences in learning rather than motor capabilities.

Instead of using rotated  $T$ s and  $L$ s for target and distractor stimuli, respectively, the participants were required to detect and identify as quickly and accurately as possible an even number presented among distractors, which were odd numbers. The target numbers (2, 4, 6, or 8) were presented among seven distractor stimuli of the same numerical identity (1s, 3s, 5s, or 7s). Participants responded by pressing buttons corresponding to the target's numerical identity



**Figure 1.** Examples of the stimuli presented to participants in the contextual cueing (CC) task. On the left, the target is 8, and the distractors are 1s; on the right, the target is 2, and the distractors are 5s. To view a colour version of this figure, please see the online issue of the Journal.

(2, 4, 6, or 8) on a four-button response box. Jiménez and Vázquez (2009) have also shown that learning is unaffected by replacing letter stimuli with number stimuli.

As depicted in Figure 1, on each trial there were two stimuli of each colour, with stimuli evenly distributed over the four quadrants of the display and filling 8 of 16 possible stimuli locations from a  $4 \times 4$  invisible matrix. Within a trial, all the distractors had the same numerical identity; however, the precise combination of location, identity, and colour of distractors created a context for the location of a target on each trial. A total of 40 such combinations were generated, and each context was always associated with the same target location but a changing target identity. A total of 8 high-frequency contexts were repeated frequently (24 times within each session), and 32 low-frequency contexts were repeated infrequently (on average 6 times per session). Each high-frequency context was associated with a unique target location, whilst sets of 4 low-frequency contexts were each associated with a different one of the remaining 8 possible target locations. Of the sets of 4 low-frequency contexts associated with a given target location, each context was characterized by a different distractor identity, as well as by a different distribution of locations and colours. Similarly, of the 8 high-frequency contexts, 2 contexts contained 1s, 2 contained 3s, 2 contained 5s, and 2 contained 7s and were each characterized by a different distribution of distractor locations and colours. Thus, all target locations were equally

cued, and all distractor identities, colours, and locations were equally present. However, the precise combination of distractor location, identity, and colour in the high-frequency contexts provided greater opportunity than the combinations in the low-frequency contexts for participants to be cued to the location of the target in order for the participant to determine its numerical identity.

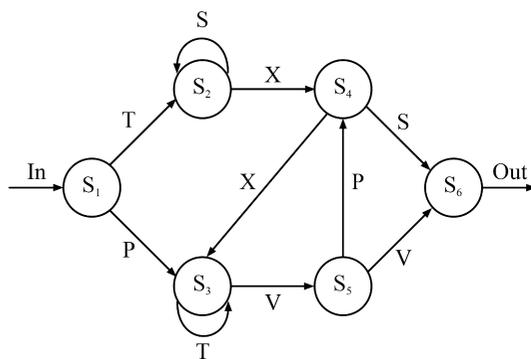
Each experimental block consisted of 48 trials. Half of all trials within a block contained high-frequency contexts and the remaining half low-frequency contexts. These different trial types (high-frequency and low-frequency contexts) were randomly intermixed for every experimental block (1–8). The session began with a short practice block, consisting of 8 low-frequency context trials, after which it was ensured that the participant had understood the demands of the task. Between each block, the experimenter provided the participant with feedback about their accuracy and reaction times (RTs). Feedback was provided following any trial on which a participant made an error, by presenting the word “error” at the top of the screen for 150 ms before the next trial was presented. At the start of each session, the solid lines creating the quadrant (see Figure 1) were presented and remained on the screen for the entire block. Each trial began with the presentation of distractors and target and was terminated following a response. Trials were separated from one another by a 50-ms response-to-stimulus interval, intended to minimize the development

of explicit strategies. Learning was measured by comparing each participant's RT in response to the high-frequency trials and the low-frequency trials.

**Serial reaction time (SRT) task.** Participants were asked to respond as quickly and as accurately as possible to a large black dot appearing in one of four locations by pressing corresponding buttons on a four-button response box. They were instructed that upon pressing the correct corresponding button, the black dot would move to another location and that they should continue the task in this fashion. The location of the dot followed a 12-digit second-order conditional sequence (312143241342), such that the subsequent location of the dot was perfectly predicted by the previous two locations (e.g., after the series 3, 1, location 2 is expected). However, the sequence was probabilistic, so that occasionally the dot appeared in locations unpredicted by this sequence. These improbable trials were generated randomly on 15% of trials, by following the constraints of an alternative second-order sequence (132341243142). Thus, in those trials, the series 3, 1 would not be followed by 2, but rather by 4, as stipulated in this alternative series (Schvaneveldt & Gomez, 1998). The response-to-stimulus interval was programmed at 0 ms and, together with the use of a probabilistic second-order sequence, was employed to minimize the use of explicit strategies during learning (Destrebecqz & Cleeremans, 2003). There were nine blocks of trials: The first was a baseline block, consisting of 48 trials during which both sequences were equally likely; the remainder consisted of 120 trials each with 15% of improbable trials, as described above. Between each block, the experimenter provided the participant with feedback about their accuracy. Sequence learning was assessed by comparing participants' RT between trials that were generated according to the frequent sequence (i.e., probable trials) and those that were generated by the alternative sequence (i.e., improbable trials).

**Artificial grammar learning (AGL) task.** During a learning phase, participants were told that they would be presented with a series of nonsense letter strings, which they should memorize because after each letter string disappeared they would need to reproduce it using the keyboard. Each string was presented for four seconds. When reproducing the strings, upon typing an incorrect letter, participants were instructed: "Incorrect. Please try again." Participants were then presented with the string for another four seconds before trying again to reproduce it. In total, 20 different strings were presented during this learning phase; each was presented twice, once in one of two blocks, which were separated by a short interval. Crucially, all the learning strings conformed to an artificial, semantic-free, finite-state grammar (see Figure 2). To elaborate, grammatical strings are created by following the direction of the arrow, and a letter is added to the string whenever a node is passed (e.g., PTTTVPS or TSXXTTVV). These learning strings were replicated exactly from the stimuli reported in A. S. Reber et al. (1991) and A. S. Reber (1993). Thus, letter strings were between 3–8 letters long, and strings were selected so that all the variations of the grammar, the three loops, and all possible beginnings and endings were displayed (see A. S. Reber et al., 1991).

Instructions up to the end of the learning phase described a memory experiment; the



**Figure 2.** Schematic diagram of the artificial, finite-state grammar used to produce stimuli for the artificial grammar learning (AGL) task. Adapted from Reber et al. (1991).

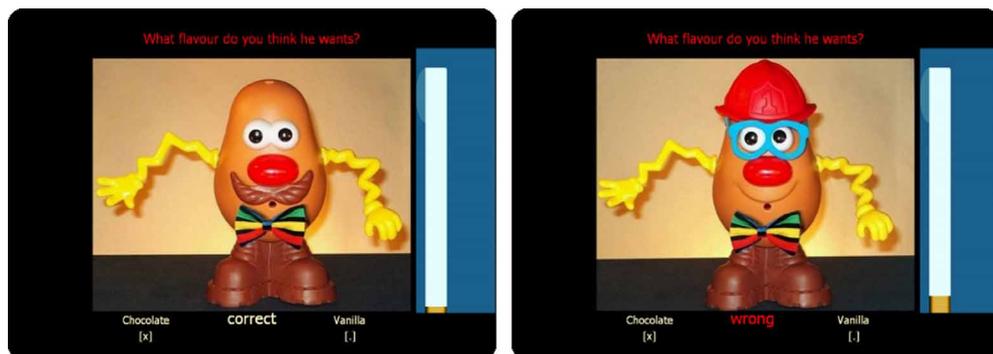
grammaticality of the strings was unknown to the participants. Upon beginning the test phase, participants were told that those strings had followed rules. Participants were further instructed that they would now see letter strings, some of which followed the rules and some of which did not, and that they would have to judge, according to their first feeling, whether they followed the rules. Test strings were presented one at a time, for a maximum of 6 seconds, and participants indicated yes if they felt a string followed the rules by pressing “Y” or no if they felt it did not by pressing “N”. Test stimuli consisted of 25 grammatical letter strings (7 of which were old strings from the learning set, and the remaining were novel grammatical strings) and 25 nongrammatical letter strings, which were formed by introducing one or more violations into otherwise grammatical letter strings (see A. S. Reber et al., 1991). Overall, grammar learning was assessed by comparing classification performance against chance performance.

**Probabilistic classification learning (PCL) task.** We used a version of the PCL task developed by Aczél (2006) and Shohamy et al. (2004). During a learning phase, participants were told that they would be selling ice cream in an ice cream shop and that “customers” would come in to buy vanilla or chocolate ice cream cones (Figure 3).

Each time a customer would visit, they would have to try to guess whether the customer would like vanilla or chocolate. After each guess of vanilla or chocolate, participants received feedback on which flavour the customers would have preferred (outcome); the word “correct” in white or “wrong” in red were displayed at the bottom of the screen for 600 ms, followed by a blank screen for 100 ms. The customers (stimuli) were displayed for 500 ms before participants could respond; participants responded by pressing the “Z” key to guess chocolate and the “.” key to guess vanilla. Participants were prompted to “please respond now” after 1,500 ms, and the trial timed out with the message “no response” after 5,000 ms. When participants responded correctly, a coin was added to their “tip jar” in the ice cream shop.

Mr Potato Head toy photographs (Figure 3) were used as the stimuli that appeared on each trial. A total of 14 different stimuli were created by changing the presence or absence of four discrete cues on the basic Mr Potato Head figure (e.g., moustache or glasses). The combination of cues used was identical to those used by Shohamy et al. (2004) and is shown in Table 2.

Using the 14 stimuli, 214 trials were constructed for the learning phase. As a consequence of the feedback, each stimulus became



**Figure 3.** Illustration of probabilistic classification learning (PCL) task. Presented above are computer screengrabs from the moment after a participant had made their guess during the learning phase, either correctly (as depicted in the left screengrab) or incorrectly (as depicted in the right screengrab). The screengrabs show two different examples of stimuli (the stimulus on the left has Cue 1 and Cue 4 present, the stimulus on the right has Cue 2, Cue 3, and Cue 4 present—see Table 2). To view a colour version of this figure, please see the online issue of the Journal.

**Table 2.** *The stimuli and probability structure of the PCL task*

<i>Stimulus</i>	<i>Cue 1</i>	<i>Cue 2</i>	<i>Cue 3</i>	<i>Cue 4</i>	$P$ ( <i>stimulus</i> )	$P$ ( <i>vanilla stimulus</i> )
A	0	0	0	1	.136	.143
B	0	0	1	0	.079	.375
C	0	0	1	1	.089	.111
D	0	1	0	0	.079	.625
E	0	1	0	1	.061	.167
F	0	1	1	0	.061	.667
G	0	1	1	1	.042	.250
H	1	0	0	0	.136	.857
I	1	0	0	1	.061	.333
J	1	0	1	0	.061	.833
K	1	0	1	1	.033	.333
L	1	1	0	0	.089	.889
M	1	1	0	1	.033	.667
N	1	1	1	0	.042	.750

*Note:* PCL = probabilistic classification learning. Cue 1 = brown moustache, Cue 2 = red hat, Cue 3 = blue glasses, Cue 4 = bow tie. Each cue could be present (1) or absent (0) for each pattern. The all-present (1111) and all-absent (0000) patterns were never used. On any trial during the learning phase, there was a given probability of each of the 14 stimuli appearing— $P(\text{stimulus})$ —and a dynamic stimulus–outcome probability for each of these 14 stimuli. During the test phase, when feedback is removed, the stimulus–outcome probability is static— $P(\text{vanilla}|\text{stimulus})$ . All stimuli appeared equally often during the test phase. The overall probability of the vanilla outcome across all stimuli is 50%.

probabilistically associated with an outcome. Across the entire learning phase the two outcomes (preference for vanilla or chocolate) were equally probable across all stimuli. Once participants had completed the learning phase, they undertook the test phase, which was identical to the learning phase with the exception that feedback was no longer provided. With the removal of feedback about the outcome, participants were required to rely on the probabilities between the stimuli and outcomes (stimulus–outcome probabilities) that they had experienced during the learning phase. The stimulus–outcome probabilities between the stimuli varied from near chance (62.5%) to almost certain (88.9%), as detailed in Table 2. The test phase consisted of 70 trials with each of the 14 stimuli being shown 5 times. Trials presenting the 14 different stimuli were randomly intermixed during both learning and test phases. Both the percentage of correct guesses, according to which outcome was more likely (above 50%), and the extent to which this percentage correct matched with the stimulus–outcome probabilities were taken as indices of learning.

#### *The explicit task*

**Paired-associates learning (PAL) task.** Participants were instructed that they should try to learn a series of three-letter word pairs (e.g., bun–cab). During this learning phase, they were shown the first word of a pair for 2,500 ms and then the second word such that both words were on screen for a further 2,500 ms. Participants were shown a total of 15 word pairs in this way, with a response-to-stimulus interval of 200 ms. In the following test phase, participants were sequentially presented with the first word from each of the pairs and were instructed to provide the word with which it was paired, or to skip the trial if they had not learnt the pair. If the response was correct, the message “Correct!” immediately appeared on the screen and remained together with the correct word pair for 2,500 ms. An incorrect response yielded the message “Wrong!” with the simultaneous replacement of the incorrect word with the correct answer, and together the message and pair remained for 2,500 ms. This whole process was repeated four times. Pairs appeared in the same order between equivalent

learning and testing blocks, but pair order was randomized across blocks (e.g., pair order was the same for Learning 1 and Testing 1 but different between Learning and Testing 1 and Learning and Testing 2). Learning is indexed by the number of pairs correctly reproduced in each test phase (Underwood, Boruch, & Malmi, 1978). All words were one-syllable, three-lettered, not infrequent (Thorndike & Lorge, 1944), and regularly spelt, concrete nouns. All words had an age of acquisition of less than 7 years according to either Morrison, Chappell, and Ellis's (1997) norms or acquired teacher ratings (which correlated well with Morrison et al.'s, 1997, limited norms,  $r = .82$ ,  $p = .01$ ,  $r^2 = .67$ ).

### *General procedure*

All testing was conducted at the participants' schools, and participants were tested individually in quiet, unused classrooms. Each session lasted approximately 50 min with participants taking as many sessions as necessary to complete the tasks, with the constraint that no session would break up a task. Most participants completed the tests within three or four sessions, and a minority (2 children) completed testing within five sessions. For all the computerized tasks, participants were seated approximately 50 cm away from the laptop. Prior to each task, they were provided with written and oral instructions. The WASI was administered according to the standardized testing procedure. Task and trial order were fixed across participants because the between-group comparison was most important, and such fixing minimizes the relevant noise and facilitates the most precise and accurate comparison. Further, the order in which the tasks were completed were carefully selected in order to minimize the possibility of priming participants into an explicit mindset, as it has been demonstrated that explicit instructions increase the contribution of explicit processes on implicit procedures (e.g., Gebauer & Mackintosh, 2007). Therefore, participants completed the tasks in the following order: PCL, CC, AGL, SRT, WASI IQ Test, PAL, and Explicit Interview. The Explicit Interview consisted of a post-task questionnaire about the

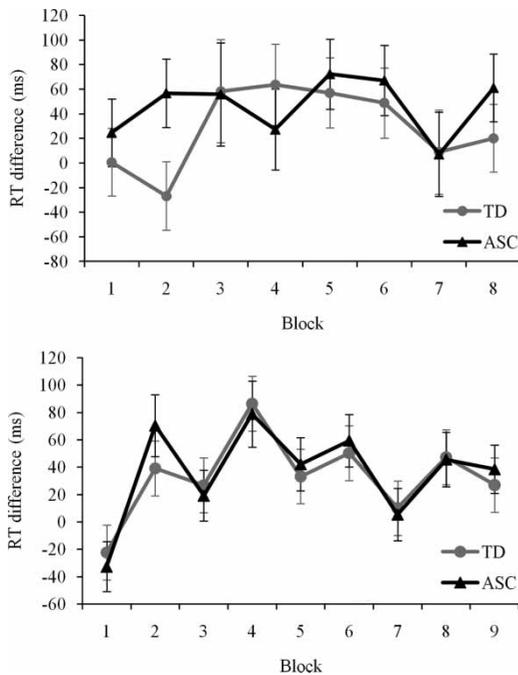
incidental structures in each of the implicit learning tasks.

## **Results**

For all analyses, the alpha level was set at .05, two-tailed, and extreme outliers (values either less than three times the interquartile range below the lower quartile or greater than three times the interquartile range above the upper quartile) were excluded. Where relevant, the appropriate epsilon correction was used when sphericity was violated. Sidak corrections were used to control for familywise error rates during multiple comparisons. Where significant interactions were found in our mixed analyses of variance (ANOVAs), separate ANOVAs on the levels of interest were conducted to establish simple effects. When conducting independent-sample  $t$  tests, equal sample variances were assumed unless Levene's test for the equality of variances was significant. Cohen's  $d$  is reported as a measure of effect size but where relative measures of effect size are more appropriate then partial eta-squared is reported. In all reported equivalence analyses (Rogers et al., 1993; Stegner et al., 1996), random within-subject variability in the TD group was used to determine the between-group equivalence threshold.

### *CC and SRT analysis*

In the RT analyses for both SRT and CC RTs on error trials were discarded. First trial data were excluded for the SRT, since meaningful assessment can only occur when the stimuli have been presented sequentially. Figure 4 represents the mean RT (ms) difference between trial types across blocks on CC (top panel) and SRT (bottom panel). A difference score greater than zero indicates that participants responded faster to the high-frequency contexts in CC and the probable trials in SRT. Clearly, there is evidence of learning: Difference scores were above zero, and, on average, difference scores after the first block tended to be greater than those on the first block. Mixed ANOVAs conducted on mean RTs supported this interpretation; each had one between-subject factor of group (ASC vs. TD)



**Figure 4.** Typically developing (TD) and autism spectrum condition (ASC) groups displayed similar learning on the contextual cueing (CC) and serial reaction time (SRT) tasks. Depicted are the mean RT differences between high- and low-frequency contexts on the CC (top panel) and probable and improbable trials on the SRT (bottom panel) across training for different groups. The error bars show twice the standard error of differences between group means at different levels of block.

and two within-subjects factors, trial type (high frequency vs. low frequency in CC and probable vs. improbable in SRT) and block (1–8 in CC and 1–9 in SRT). In both analyses, there was a main effect of trial type—CC,  $F(1, 50) = 27.74$ ,  $p < .001$ ,  $\eta^2_p = .36$ ; SRT,  $F(1, 50) = 57.25$ ,  $p < .001$ ,  $\eta^2_p = .53$ —and an interaction between Trial Type  $\times$  Block—CC,  $F(7, 328) = 2.30$ ,  $p = .03$ ,  $\eta^2_p = .04$ ; SRT,  $F(7, 350) = 11.32$ ,  $p < .001$ ,  $\eta^2_p = .19$ .

Figure 4 demonstrates that the RT difference scores for both tasks were very closely matched between the groups. Indeed, there was no evidence of group differences in learning in either analysis: On both tasks there was no Group  $\times$  Trial Type interaction—CC,  $F(1, 50) = 1.52$ ,  $p = .22$ ,

$\eta^2_p = .03$ ; SRT,  $F(1, 50) = 0.12$ ,  $p = .73$ ,  $\eta^2_p < .01$ —or between Group  $\times$  Trial Type  $\times$  Block—CC,  $F(7, 328) = 1.37$ ,  $p = .25$ ,  $\eta^2_p = .03$ ; SRT,  $F(6, 298) = 0.50$ ,  $p = .80$ ,  $\eta^2_p = .01$ . This was in spite of an actual power always more than .97 to detect even a medium effect (Cohen's  $F = .25$ ) on these relevant group interactions for both SRT and CC (calculated using G\*Power; Faul, Erdfelder, Lang, & Buchner, 2007). However, regardless of this sizeable power, in order that we did not rely on a failure to reject a null hypothesis as a reason to suppose that performance is preserved in ASC, equivalence analyses were employed to determine the equivalence of the learning (e.g., Rogers et al., 1993). Equivalence analyses were performed on average proportional increase in RT differences across blocks for both tests; this learning index was used because the analysis necessitates an overall score. The analyses rejected the hypotheses of nonequivalence for both tests—CC,  $t(50) = 3.35$ ,  $p < .001$ ; SRT,  $t(50) = 1.81$ ,  $p = .04$  (see Appendix)—and allowed the conclusion that the groups are statistically equivalent in their overall learning on each task.

On both tasks, the ASC group were generally slower to respond and more variable reflective of typical motor difficulties (e.g., Allen, Müller, & Courchesne, 2004; Dowell, Mahone, & Mostofsky, 2009). To examine whether such differences in speed and variability may have masked any other differences in learning, two transformations are possible: Barnes et al. (2008) suggest transforming the dependent variable into a measure that expresses learning as a proportion of baseline speed (the difference in speed between trial types/mean speed on low-frequency or improbable trials); Jiménez and Vázquez (2008) suggest  $z$  score transformation as a means of better analysing group differences in learning on implicit RT tasks. Nonetheless, analyses of both transformations provided exactly the same pattern of results, thereby reinforcing the conclusion that the groups were equivalent in their amount of overall learning on both the SRT and CC.

In the original mixed ANOVAs of the CC and SRT, there was a main effect of block—CC,  $F(4, 219) = 18.24$ ,  $p < .001$ ,  $\eta^2_p = .27$ ; SRT,  $F(4,$

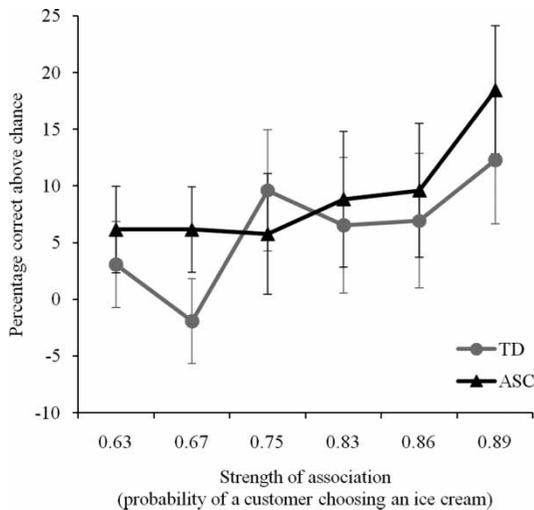
211) = 18.04,  $p < .001$ ,  $\eta^2_p = .27$ —together with a linear contrast for RT to decrease across blocks—CC,  $F(1, 50) = 44.99$ ,  $p < .001$ ,  $\eta^2_p = .47$ ; SRT,  $F(1, 50) = 44.32$ ,  $p < .001$ ,  $\eta^2_p = .47$ . These decreases in RT across block were expected and reflected improvement in performance due to practice effects rather than learning about the context or sequence as they are independent of trial type. Furthermore, on the SRT there was an interaction between Group  $\times$  Block,  $F(4, 211) = 4.15$ ,  $p < .01$ ,  $\eta^2_p = .08$ , but not on the CC,  $F(4, 219) = 0.97$ ,  $p = .43$ ,  $\eta^2_p = .02$ . Inspection of the data implied that the ASC group seemed to benefit more from practice on the SRT: During the initial blocks the ASC group were slower than the TD group but during the later blocks, once there had been sufficient opportunity for practice, the groups responded equally quickly. Consistent with this interpretation, there was a significant linear contrast for the differences between groups to become smaller as blocks progressed,  $F(1, 50) = 6.34$ ,  $p = .02$ ,  $\eta^2_p = .11$ . Simple effects analyses of the Group  $\times$  Block interaction, investigating the effect of block in each group separately, established a practice effect in both groups: TD, main effect of block,  $F(5, 122) = 9.26$ ,  $p < .001$ ,  $\eta^2_p = .27$ , with a significant linear contrast for RTs to decrease,  $F(1, 25) = 20.49$ ,  $p < .001$ ,  $\eta^2_p = .45$ ; ASC, main effect of block,  $F(3, 83) = 11.97$ ,  $p < .001$ ,  $\eta^2_p = .32$ , with a significant linear contrast for RTs to decrease,  $F(1, 25) = 26.61$ ,  $p < .001$ ,  $\eta^2_p = .52$ . Thus, it seems that while both groups benefited from practice, children with ASC benefited to a greater extent. In order to establish that this pattern of results was not simply a consequence of group trends for different RT means and variances, the data were considered as proportions and  $z$  scores. However, the same pattern of results persisted, reinforcing the conclusion that the group with ASC benefited from practice more than the TD group did and that this was independent of learning about the context or sequence.

There was a small percentage of errors on the SRT, and these errors were similar between the groups—TD,  $M = 8.42\%$ ; ASC,  $M = 9.12\%$ ;

standard error of difference,  $SED = 1.03$ ;  $t(50) = 0.67$ ,  $p = .50$ ,  $d = 0.17$ . Since Song, Howard, and Howard (2007) have shown that errors on the SRT also index learning, the SRT error data were subjected to the same analyses as RTs. However, the results of the two analyses were entirely consistent with one another, and thus it was deemed unnecessary to report both analyses. There was also a small percentage of errors on the CC with the ASC group making significantly fewer errors than the TD group—TD,  $M = 6.93\%$ ; ASC,  $M = 2.95\%$ ;  $SED = 0.94\%$ ;  $U = 134.00$ ,  $p < .001$ ,  $d = 1.18$ . However, the difference in errors between trial types has been found not to index learning on the CC task (e.g., Chun & Jiang, 1998, 2003). We replicated that finding—mean difference between trial type =  $-0.13\%$ ,  $SEM = 0.28\%$ ;  $t(51) = 0.47$ ,  $p = .64$ ,  $d = 0.06$ —and also found that there was no evidence of a group difference in this tendency—TD,  $M = 0.08\%$ ; ASC,  $M = 0.18\%$ ;  $SED = 0.56\%$ ;  $t(50) = 0.18$ ,  $p = .86$ ,  $d = 0.05$ . Therefore, the superior overall accuracy of the ASC group provides no evidence of differences in learning and is instead likely to reflect that ASC individuals sometimes display enhanced perceptual functioning (Motttron et al., 2006).

#### *AGL and PCL analysis*

In both AGL and PCL, the dependent variable was percentage correct above chance during their respective test phases (50%). For the AGL, an answer that accurately classified a string (“Yes” to grammatical strings and “No” to ungrammatical strings) was deemed correct. For the PCL, a guess that corresponded with the more likely outcome for that stimulus was judged correct. One-sample  $t$  tests demonstrated the basic learning effect in both the PCL— $M = 6.84\%$ ,  $SEM = 1.36\%$ ;  $t(51) = 5.05$ ,  $p < .001$ ,  $d = 0.70$ , and AGL— $M = 3.28\%$ ,  $SEM = 1.12\%$ ;  $t(51) = 2.93$ ,  $p = .005$ ,  $d = 0.41$ . Independent-sample  $t$  tests on the group means provided no evidence of a difference between the groups for both the PCL—TD,  $M = 4.95\%$ ; ASC,  $M = 8.74\%$ ,  $SED = 2.68\%$ ;  $t(41) = 1.41$ ,  $p = .17$ ,  $d = 0.39$ , and the AGL—TD,  $M = 3.35\%$ ; ASC,  $M = 3.20\%$ ,



**Figure 5.** Typically developing (TD) and autism spectrum condition (ASC) groups showed similar learning about more likely outcomes on the probabilistic classification learning (PCL) task. Presented are mean percentage of correct guesses that were provided above chance by participants on the PCL test phase. This score is presented for the two groups at the different levels of stimulus–outcome probability. The error bars show twice the standard error of differences between group means at different levels of stimulus–outcome probability.

$SED = 2.26\%$ ;  $t(50) = 0.07$ ,  $p = .94$ ,  $d = 0.02$ .<sup>1</sup> Furthermore, subsequent equivalence analyses (e.g., Rogers et al., 1993) rejected the hypotheses of nonequivalence—PCL,  $t(50) = 3.37$ ,  $p < .01$ ; AGL,  $t(50) = 4.489$ ,  $p < .001$ —and allowed the conclusion that the groups were statistically equivalent in their overall learning on each task.

To consider the PCL performance in greater detail, percentage correct above chance was considered at different levels of stimulus–outcome probability. Figure 5 demonstrates that percentage correct increased with the stimulus–outcome probability and that the two groups’ performance was closely matched. A mixed

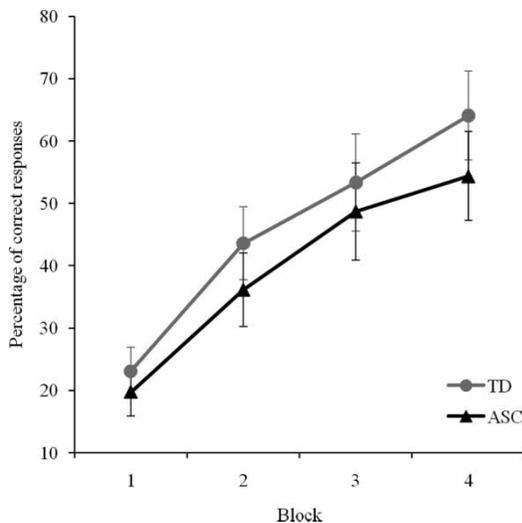
ANOVA was conducted, with one between-subject factor of group (ASC and TD) and one within-subject factor of stimulus–outcome probability (probabilities of .63, .67, .75, .83, .86, & .89). A main effect of stimulus–outcome probability,  $F(4, 185) = 3.72$ ,  $p = .01$ ,  $\eta^2_p = .07$ , together with a significant linear contrast for percentage correct to increase with probability,  $F(1, 50) = 10.35$ ,  $p < .01$ ,  $\eta^2_p = .17$ , established that participants learnt more about more likely outcomes, while there was no evidence of group differences: group,  $F(1, 50) = 1.09$ ,  $p = .30$ ,  $\eta^2_p = .02$ ; Group  $\times$  Stimulus–Outcome Probability,  $F(4, 185) = 0.77$ ,  $p = .54$ ,  $\eta^2_p = .02$ . The performance of participants during the learning phase of the PCL was also considered, in order to investigate the development of the learning. Feedback was still provided during the learning phase, so stimulus–outcome probability was not fixed and is not considered in this part of the analysis. However, for every trial included in this analysis, a stimulus was always more strongly associated with one outcome than the other, and therefore an assessment of performance during the learning phase is still meaningful. For this purpose, the learning phase was split into four blocks (excluding the first presentation of stimuli and any trial on which stimulus–outcome probability was 50%): Trials 1–48, 49–96, 97–145, and 146–194. A mixed ANOVA was conducted on the percentage correct above chance during the PCL learning phase, with one between-subject factor of group (ASC and TD) and one within-subject factor of block (Block 1–4). A main effect of block,  $F(3, 150) = 2.76$ ,  $p = .04$ ,  $\eta^2_p = .05$ , together with a linear trend for performance to increase, showed that learning emerged across training. Again there was no evidence of any differences between the groups: group,  $F(1, 50) = 0.76$ ,  $p = .39$ ,  $\eta^2_p = .02$ ; Group  $\times$  Block,

<sup>1</sup> The comparison of novel versus repeated test strings yielded no theoretically meaningful results as a consequence of a limited test phase. The means for repeated strings were based on participants’ answers to just seven strings, and thus performance was too variable and unreliable to establish whether there were any mechanistic differences in how equivalence in overall performance was achieved. Further research might include a prolonged test phase with an equal number of novel and repeated strings in order to assess this question.

$F(3, 150) = 0.02, p > .99, \eta^2_p < .01$ . Strategy analysis (e.g., Gluck et al., 2002) was also performed on these data and revealed no evidence of differences in the distribution of individual response strategies between the two groups.

### PAL analysis

The dependent variable was the percentage of correct responses given during the test blocks. The provision of a word pair that corresponded with its cue constituted a correct response. Each test block was preceded by a learning block. Therefore, the increase in performance across test blocks represented an improvement in performance due to learning (see Figure 6). A mixed analysis of variance, with one between-subject factor of group (ASC vs. TD) and one within-subject factor of block (4 levels) supported this interpretation: a main effect of block,  $F(2, 102) = 80.73, p < .001, \eta^2_p = .62$ , together with a significant linear contrast with performance increasing across blocks,  $F(1, 50) = 133.90, p < .001, \eta^2_p = .73$ ,



**Figure 6.** The typically developing (TD) group displayed a numerically, but not statistically, superior performance to the autism spectrum condition (ASC) group on the paired-associates learning (PAL) task. Depicted are mean percentage of correct responses that participants from different groups provided on test blocks in the PAL task. The error bars show twice the standard error of differences between group means at different levels of block.

established that learning had occurred. While the TD group numerically outperformed the ASC group on every test block (see Figure 6), there was no evidence for an effect of group,  $F(1, 50) = 1.30, p = .26, \eta^2_p = .03$ , nor for an interaction of Group  $\times$  Block,  $F(2, 102) = 0.62, p = .54, \eta^2_p = .01$ . However, subsequent equivalence analysis on overall test performance revealed there was also no evidence of equivalence,  $t(50) = 0.76, p = .22$ .

In order to explore this discrepancy between the results from the mixed ANOVA and those of the equivalence analysis on the PAL, we considered the possible role of IQ in implicit and explicit learning in our tests. We therefore conducted a series of analyses on all the tests but this time including an additional 5 children per group. Whilst the addition of these extra children resulted in the same mean age and gender between groups, the groups were no longer matched on IQ (see “Entire Sample” in Table 1 for participant characteristics). The analysis of the PAL data revealed that the ASC group performed worse than the TD group—TD,  $M = 50.70\%$ ; ASC,  $M = 39.41\%$ ,  $SED = 5.39\%$ ; main effect of group,  $F(1, 60) = 4.39, p = .04, \eta^2_p = .07$ —with the TD group outperforming the ASC group at every level. However, in contrast, all analyses of all implicit learning tests on the entire groups unmatched for IQ showed an identical pattern of preservation of implicit learning to those conducted on the matched groups. Finally, there was one further finding that also suggested that explicit processing may be more problematic than implicit processing in ASCs. During the learning phase of the AGL, the mean number of errors that participants made before correctly reproducing each letter string was significantly greater in ASC than TD participants: TD,  $M = 1.00$ ; ASC,  $M = 1.48$ ,  $SED = 0.20$ ,  $t(36) = 2.47, p = .02, d = 0.68$ . Unsurprisingly, this result was the same, although the effect was more pronounced, when the groups were unmatched for IQ. These errors are indicative of a participant’s ability to explicitly remember and reproduce letter strings in the short term and have been used previously as a measure

of explicit processing that is related to IQ (e.g., A. S. Reber et al., 1991). These explicit processes are separate to those processes mediating implicit learning performance on the AGL (e.g., A. S. Reber et al., 1991). Indeed, the errors were not related to implicit learning on the AGL task in either group even when the two groups were considered as the entire sample (see Table 1); TD,  $r = -.40$ ,  $n = 31$ ,  $p = .06$ ,  $r^2 = .16$ ; ASC,  $r = .02$ ,  $n = 31$ ,  $p = .99$ ,  $r^2 < .01$ .

### *Explicit interviews*

Post-task questionnaires indicated that participants of both groups could not freely report what they had learnt on the CC, SRT, AGL, and PCL tasks. No further attempts were made to establish quantitatively the extent to which the products of learning were consciously retrievable because it was feared such post-task probing would encourage explicit strategies on subsequent implicit learning tasks (Gebauer & Mackintosh, 2007). Also, consistent with our interpretation that performance was implicit on these versions of the implicit learning tasks, there was no evidence of a correlation between performance on the implicit learning tasks and IQ in neither the TD nor the ASC group. This was true even when the groups were considered as an entire sample and therefore contained a large range of IQs (see Table 1); TD, range of Pearson's  $r = -.08$  to  $.32$ ,  $n = 31$ ,  $ps > .05$ ,  $r^2 \leq .10$ ; ASC, range of Pearson's  $r = .08$  to  $.40$ ,  $n = 31$ ,  $ps > .05$ ,  $r^2 \leq .16$ .

### *SCQ analysis*

The relationships were analysed between scores on the SCQ and overall indices of learning from each task (the average proportional increase in RT differences across blocks was used for CC and SRT; mean percentage correct above chance during test phase was used for the AGL and PCL; mean percentage of correct responses given during test was used for the PAL). In the IQ-matched subgroups (see Table 1) there was no evidence of correlation between SCQ-scores and any of the learning tasks in either group; TD: range of Pearson's  $r = -.24$  to  $.27$ ,  $n = 19$ ,  $ps > .05$ ,

$r^2 \leq .07$ ; ASC: range of Pearson's  $r = -.23$  to  $.20$ ,  $n = 15$ ,  $ps > .05$ ,  $r^2 \leq .05$ . Similarly, there was no evidence of correlation between SCQ-scores and learning tasks in the entire sample of children, who were not matched for IQ (see Table 1); TD, range of Pearson's  $r = -.27$  to  $.28$ ,  $n = 23$ ,  $ps > .05$ ,  $r^2 \leq .08$ ; ASC, range of Pearson's  $r = -.17$  to  $.18$ ,  $n = 18$ ,  $ps > .05$ ,  $r^2 \leq .03$ ).

## Discussion

Performance on the implicit learning tasks reported here is preserved in ASC. Implicit learning was intact across a number of tasks that differed in surface features, each feature being in some way relevant to certain features of ASC: The PCL had a social element to it, involving cartoon faces and characters; the SRT required motor coordination; the CC task involved perceptual processing of context; and it has been argued that the AGL's artificial grammar is related to language (e.g., Gomez & Gerken, 2000). Thus, in contrast to previous studies, we found no deficits in implicit learning in ASC and suggest that a general deficit in implicit learning processes is not present in ASC. Furthermore, implicit learning ability was not related to an index of ASC symptomatology, the SCQ (Rutter et al., 2003). Together, these findings undermine the argument that such a deficit might play a key role in the social, communicative, or motor impairments (e.g., L. G. Klinger et al., 2007; Mostofsky et al., 2000).

Our findings converge with other recent reports of intact implicit learning in ASC. For example, Barnes et al. (2008) found preservation on the SRT and CC, Kourkoulou, Findlay, and Leekam (2009) on the CC, and Müller, Cauch, Rubio, Mizuno, and Courchesne (2004), Smith, Reber, Schmeidler, and Silverman (2008), and Travers, Klinger, Klinger, and Mussey (2008) on the SRT. Further, it is consistent with intact performance on related incidental procedures such as implicit memory and priming (Bowler, Matthews, & Gardiner, 1997; Gardiner, Bowler, & Grice, 2003; Renner, Klinger, & Klinger, 2000).

This raises the question of possible reasons for the discrepancy with other studies that have

reported implicit learning deficits (Gordon & Stark, 2007; L. G. Klinger & Dawson, 2001; L. G. Klinger et al., 2007; Mostofsky et al., 2000). One possibility that has been suggested by others is that the observation of intact implicit learning has been obscured in some studies as a consequence of poor matching of IQ between the group with ASC and comparison groups (Soulières, Mottron, Saugier, & Larochelle, 2007). For example, in those studies in which deficits have been reported, the groups of children with ASC had overall lower IQ scores (Gordon & Stark, 2007; L. G. Klinger & Dawson, 2001; L. G. Klinger et al., 2007; Mostofsky et al., 2000), raising the possibility that the deficit in implicit learning resulted from reduced overall general mental functioning. Interestingly, we did not find support for this possibility in our study: When we included further individuals in our analysis, such that the ASC group's average IQ score was lower than that of the typically developing group (see Table 1), the evidence of intact implicit learning in the ASC group remained. In direct contrast, comparing these two larger groups unmatched for IQ revealed deficits in ASC in explicit learning (PAL test). This observation suggests two important points. First, it reinforces the finding that IQ and explicit learning are intimately related, whilst implicit learning is relatively independent (e.g., Gebauer & Mackintosh, 2007, 2009; Kaufman et al., 2009; A. S. Reber et al., 1991). Second, the intact implicit learning observed in this study cannot be accounted for by IQ or compensations for poor implicit learning by the use of explicit strategies (cf. L. G. Klinger et al., 2007).

Another strong possibility is that the discrepancy between recent studies and the earlier ones reporting a deficit in implicit learning results (at least in part) from differences in the particulars of the tasks and stimuli employed, rather than from genuine differences in implicit learning ability between children with and without ASC. In particular, studies that have documented impairment in implicit learning have used procedures that seemed to have allowed for the greater use of explicit strategies (e.g., long

response-to-stimulus intervals and deterministic sequences on the SRT, Gordon & Stark, 2007; nonprobabilistic category learning, L. G. Klinger & Dawson, 2001; L. G. Klinger et al., 2007; Mostofsky et al., 2000). When both children with ASC and TD children use explicit, rather than implicit, strategies to solve the tasks, then the impairments in the groups with ASC may well be accounted for by a poorer explicit, rather than implicit, learning performance. This seems a particularly compelling explanation given that (a) explicit, but not implicit, learning is closely related to IQ, (b) these studies reporting deficits included groups of children with ASC with lower IQ than that of the comparison groups, and (c) our finding that children with ASC with lower overall IQ than TD children showed deficits in explicit learning in our entire sample analysis of explicit learning. Further, our results also demonstrate that when implicit learning procedures are used that prevent explicit strategies from emerging, preservation is found regardless of whether the groups are matched for IQ. Whether or not there is a negative effect of explicit strategies on implicit learning tasks that is independent of IQ and unique to ASC is not clear. For example, particularly dysfunctional strategies or a dysfunctional propensity to use such strategies in ASC would cause such an effect. The worse ASC performance on the explicit processing measure taken from the training phase of the AGL would be consistent with this possibility. However, to examine this issue, it would be necessary to compare ASC individuals on an implicit learning task that encouraged explicit strategies with IQ-matched TD individuals.

A final aside that is worth emphasizing is that on average our ASC participants were high functioning. Whilst all our results, and other studies (e.g., Gebauer & Mackintosh, 2007), emphasize the independence of IQ from implicit learning, we appreciate that the interaction of low IQ and autism may be an exceptional case. Furthermore, it is now broadly recognized that high-functioning individuals with autism may constitute one of several subgroups of individuals with autistic symptoms, and that the generalizability of research

results from this subgroup to another is an issue that can only be assessed empirically and cannot be assumed.

In summary, we propose that the experiments presented here demonstrate that implicit learning is intact in ASC. Further, we propose that the impairments observed in some other studies of implicit learning can be accounted for by the procedural details of the tasks employed, which resulted in the use of explicit strategies and therefore disadvantaged the ASC groups that were not matched for IQ. Thus, in contrast to the proposal that the common “real-world” difficulties in language, social, and motor skills among individuals with ASC are caused by deficits in the implicit processes that undoubtedly underpin the acquisition of these skills, we propose that there are other processes instead that could disrupt the operations of otherwise intact implicit learning mechanisms of individuals with ASC, thereby impacting negatively on the development of these skills. As discussed by Meltzoff et al. (2009), what children learn implicitly is the product of a complex interaction between a variety of influences and is therefore not simply contingent upon the functioning of general implicit learning processes.

One possibility is that the real-world “implicit” impairments may result from a greater propensity for individuals with ASC to use explicit strategies rather than to rely on implicit strategies. Indeed, there is much evidence that for the implicit acquisition of skills to proceed normally, implicit learning must not be out-competed or obstructed by explicit strategies (e.g., Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Foerde, Knowlton, & Poldrack, 2006; Gebauer & Mackintosh, 2007; Hoyndorf & Haider, 2008; Lieberman, Chang, Chiao, Bookheimer, & Knowlton, 2004; Lleras & Von Mühlénen, 2004; Poldrack & Rodriguez, 2004). Therefore, an ASC propensity to approaching problems using explicit strategies might be sufficient to cause real-world impairment. In line with this possibility, there is evidence that ASC individuals are prone to completing learning tasks more explicitly than TD individuals (Gidley Larson & Mostofsky, 2008; L. G. Klinger et al.,

2007). In addition to this direct evidence, there are many other studies showing that ASC individuals are more prone to solving tasks explicitly (e.g., theory of mind performance is mediated explicitly in ASC; Happé, 1995; Hill & Frith, 2003). Therefore if, as we have suggested, explicit strategies are overused, then these strategies may interfere with the capacity to learn language, social, and motor skills implicitly. This would be particularly pronounced if this imbalance was combined with the use of atypical explicit strategies, which we have argued above may be the case in ASC.

Another possibility is that the well-documented unusual attention allocation in ASC may disrupt appropriate sampling of the relevant features of the real-world situation for implicit learning to proceed (Courchesne et al., 1994; Happé & Frith, 2006; Klin, Jones, Schultz, Volkmar, & Cohen, 2002). Indeed, on an adapted version of the contextual cueing procedure, in which the local context was random, and only the global context cued participants, ASC performance was found to be inferior to TD performance (M. R. Klinger, Klinger, Travers, & Mussey, 2008). This might be explained by an ASC attentional preference of the local over the global context (Happé & Frith, 2006) that obstructed the learning. Since our research documents preserved implicit learning mechanisms in ASCs, it predicts that there might be superior performance by individuals with ASC on implicit learning tasks in which the relevant features for learning are those to which individuals with ASCs have an attentional bias (Heaton & Wallace, 2004; Mottron et al., 2006). In line with this speculation, Kourkoulou et al. (2009) demonstrated enhanced implicit learning of the local context in the contextual cueing paradigm. Further, in a more ecologically valid example, Grossman and Tager-Flusberg (2008) demonstrated enhanced performance on a task involving mouth expertise—an area of the face to which ASC individuals allocate an unusual amount of attention.

Another possible explanation of ASC difficulties in real-world skills that are associated with

an implicit acquisition is that implicit learning mechanisms themselves are intact, but the knowledge derived from implicit learning is not applied successfully. This possibility cannot be assessed by the standard implicit procedures that demonstrate learning by indirect assessments or forced choices, since in the real world the products of implicit learning must be utilized in ways above and beyond those demanded by these laboratory procedures. For example, according to a theory that understands implicit learning within a graded consciousness framework (Cleeremans, 2006; Cleeremans & Jiménez, 2002), there is further utility to the capacity to learn implicitly when there is potential for its products to emerge into awareness and under cognitive control. Equally, in line with ideas and theorizing on the role of implicit learning in intuition (Eraut, 2004; Hogarth, 2001), there would also be further advantage to the capacity to learn implicitly if it exists in tandem with an ability to know when to act on the implicitly acquired knowledge. Thus, if individuals had difficulties with either of these related capacities, then they would present with difficulties in everyday abilities associated with implicit acquisition, regardless of the learning mechanism itself. Although this is a unique hypothesis in relation to implicit learning in ASC, we are not the first authors to allude to a relevant dissociation between ability and application in ASC (e.g., Minshew, Meyer, & Goldstein, 2002; Soulières et al., 2007). Further, consistent with this discussion, ASC impairment in the successful application of implicitly acquired information would tessellate with “a recent shift toward understanding ASC in the context of dysfunctions in introspection or self-referential processing” (Chiu et al., 2008, p. 468; e.g., Ben Shalom et al., 2006; Hill, Berthoz, & Frith, 2004; Iacoboni, 2006; Kennedy, Redcay, & Courchesne, 2006; Lind & Bowler, 2008; Rieffe, Meerum Terwogt, & Kotronopoulou, 2007; Russell, 1997; Toichi, 2008; Williams & Happé, 2009).

Finally, we raise the possibility that there might be impairments in the long-term consolidation of skills associated with an implicit acquisition in ASC. Studies have emphasized the crucial

importance of consolidation, or offline learning, to further improvement after implicit learning, and the role of sleep for determining the relative improvement of implicit and explicit learning contributions (for a review, see Song, 2009). In particular, sleep seems particularly relevant to the subsequent development of insight from implicit learning episodes (Wagner, Gais, Haider, Verleger, & Born, 2004). ASC is highly associated with sleep difficulties (American Psychiatric Association, 1994). Therefore, ASC differences in the consolidation of implicitly learnt information may account for some of the ASC deficits in everyday skills associated with implicit acquisition.

In conclusion, our data together with that from a number of other researchers (Barnes et al., 2008; Kourkoulou et al., 2009; Müller et al., 2004; Smith et al., 2008; Travers et al., 2008) suggest that individuals with ASC can learn implicitly and that it is unlikely that such processes are directly responsible for related real-world impairments in language, social, and motor skills. We acknowledge that ASC deficits on implicit learning tasks have also been documented, but we argue that this is due to differences in task procedures, in particular, procedures that promoted the use of explicit strategies and therefore disadvantaged the ASC groups that were not matched for IQ. Finally, we have presented hypotheses as to why there may be problems in real-world areas related to implicit acquisition, such as social cognition, motor, and language skills, in spite of preserved implicit learning mechanisms: interference due to abnormal attention or the overuse of explicit strategies; difficulties with the application of implicitly acquired knowledge; and atypical consolidation following the learning.

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## APPENDIX

### Equivalence analysis

Equivalence analysis (Rogers et al., 1993; Stegner et al., 1996) necessitates the a priori specification of an equivalence threshold; this was specified as random within-subject variability in the typically developing (TD) group. This threshold was chosen using the logic that an interesting between-group difference should be at least as large as the estimated random within-subject variability. To elaborate on the notion of random within-subject variability: If a test measures what it purports to measure perfectly, then the two split-half scores of that test would correlate perfectly with one another. Yet, in spite of no conceptual difference between two split-halves—they are randomly derived halves of the same test—usually such scores do not correlate perfectly. Consequently, the variability in one split-half score that cannot be explained by variability in the other split-half score is determined to be random within-subject variability. Therefore, the equivalence threshold = estimated random within-subject variability =  $[(1 - r^2) * \text{Var}_x * (n - 1)/(n - 2)]^{0.5}$ ;  $\text{Var}_x$  = variance on one split-half,  $r$  = correlation between the split halves. The null hypothesis would then be tested that the difference between the groups is at least as large as the equivalence threshold by conducting 2 one-

tailed  $t$  tests. For example for contextual cueing (CC):

$$t(50) = [\bar{x}_{\text{TD}} - (\bar{x}_{\text{ASC}} \pm E)] / S\bar{x}_{\text{TD}} - \bar{x}_{\text{ASC}}$$

$\bar{x}_{\text{TD}} = 2.71$ ;  $\bar{x}_{\text{ASC}} = 3.05$ ; equivalence threshold (E) = random within-subject variability =  $[(1 - 0.53^2 * 20.65 * (52 - 1)/(52 - 2)]^{0.5} = 3.92\%$ .

$$t(50) = [2.71\% - (3.05 \pm 3.92)] / [3.97^2/26 + 3.76^2/26]^{0.5}$$

$$t(50) = 3.35$$

and

$$t(50) = -3.97$$

Since an investigator is interested in whether the difference between the groups is at least as large, they just need to consider the  $t$  test that yields the largest  $p$  value (i.e., just need to test the possibility of finding the smallest difference between the actual difference and the threshold, given the null hypothesis that the difference is at least as large as the equivalence threshold). Therefore, equivalence analysis rejects the hypotheses of nonequivalence: CC,  $t(50) = 3.35$ ,  $p < .01$ .