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Implicit learning as an ability

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ABSTRACT

The ability to automatically and implicitly detect complex and noisy regularities in the environment is a fundamental aspect of human cognition. Despite considerable interest in implicit processes, few researchers have conceptualized implicit learning as an ability with meaningful individual differences. Instead, various researchers (e.g., Reber, 1993; Stanovich, 2009) have suggested that individual differences in implicit learning are minimal relative to individual differences in explicit learning. In the current study of English 16–17 year old students, we investigated the association of individual differences in implicit learning with a variety of cognitive and personality variables. Consistent with prior research and theorizing, implicit learning, as measured by a probabilistic sequence learning task, was more weakly related to psychometric intelligence than was explicit associative learning, and was unrelated to working memory. Structural equation modeling revealed that implicit learning was independently related to two components of psychometric intelligence: verbal analogical reasoning and processing speed. Implicit learning was also independently related to academic performance on two foreign language exams (French, German). Further, implicit learning was significantly associated with aspects of self-reported personality, including intuition, Openness to Experience, and impulsivity. We discuss the implications of implicit learning as an ability for dual-process theories of cognition, intelligence, personality, skill learning, complex cognition, and language acquisition.

1. Introduction

The ability to automatically and implicitly detect complex and noisy regularities in our environment is a fundamental aspect of human cognition. Much of this learning takes place on a daily basis without our intent or conscious awareness, and plays a significant role in structuring our skills, perceptions, and behavior (Hassin, Uleman, & Bargh, 2005; Kihlstrom, 1987; Lewicki, Czyzewska, & Hoffman, 1987; Lewicki & Hill, 1987; Reber, 1967, 1993; Stadler & Frensch, 1997). This type of learning is often referred to as implicit learning (Reber, 1967, 1993; Stadler & Frensch, 1997) and is typically characterized by a set of automatic, associative, nonconscious, and unintentional learning processes, as distinguished from the conscious, deliberate, and reflective learning processes that are thought to be associated with executive functioning and working memory (e.g., Barrett, Tugade, & Engle, 2004).

Despite considerable interest in implicit processes, few researchers have conceptualized implicit learning as an

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ability. While researchers of the cognitive unconscious have investigated the nature of the unconscious using the experimental approach, they have tended to treat individual differences as "noise" (error or otherwise unexplained variance), or have posited that whatever individual differences in implicit cognition do exist are minimal relative to individual differences in explicit cognition (Reber, 1993; Stanovich, 2009). For example, in distinguishing between the "algorithmic mind" and the "autonomous mind", Stanovich (2009) states that "...continuous individual differences in the autonomous mind are few. The individual differences that do exist largely reflect damage to cognitive modules that result in very discontinuous cognitive dysfunction such as autism or the agnosias and alexias (p.59)." As a consequence of these long-held assumptions, little research has investigated whether there exist meaningful individual differences in implicit learning or the correlates of such individual differences. In the current study we investigated the association of implicit learning ability with a variety of cognitive and personality variables, building on previous research examining the relation of implicit learning to psychometric intelligence, basic cognitive mechanisms, and personality traits. We take up discussion of each association in turn.

In investigating the relation between implicit learning and intelligence, researchers have relied on measures of psychometric intelligence, defined as Spearman's general intelligence, or *g*, the common variance across disparate tests of cognitive ability (Spearman, 1904). What is the link between implicit learning and *g*? According to Reber (1989, 1993) and Reber and Allen (2000), individual differences in implicit learning should be expected to be largely independent of individual differences in psychometric intelligence. The argument is based on the assumption that implicit learning is evolutionarily older than explicit cognition, with the latter developing only with the rise of *Homo sapiens*. The older mechanisms of implicit learning are believed to have been unaffected by the arrival of explicit cognition, which includes hypothesis-guided learning and deduction, and they continue to function independently of one another today. These thoughts converge with arguments advanced by Mackintosh and colleagues (Mackintosh, 1998; McLaren, Green, & Mackintosh, 1994) that the processes underlying performance on implicit learning tasks may be automatically associative rather than cognitive in nature, and are consistent with various other dual-process theories of human cognition (Chaiken & Trope, 1999; Epstein, Pacini, Denes-Raj, & Heier, 1996; Evans & Frankish, 2009; Sloman, 1996; Stanovich & West, 2000).

Thus far, the evidence suggests that performance on implicit learning tasks is independent of differences in IQ, or at most only weakly related. Some paradigms have never shown an association with psychometric intelligence (e.g., artificial grammar learning; Gebauer & Mackintosh, 2007; McGeorge, Crawford, & Kelly, 1997; Reber, Walkenfeld, & Hernstadt, 1991), whereas for other paradigms the majority of studies have not found a significant association (e.g., serial reaction time learning; Feldman, Kerr, & Streissguth, 1995; Unsworth, Heitz, Schrock, & Engle, 2005; but see Salthouse, McGuthry, & Hambrick, 1999). The relation between IQ and one other implicit learning paradigm, which involves incidental exposure to pictures, has been investigated only once but was significant (Fletcher, Maybery, & Bennett, 2000). A possible explanation for the occasional significant association between IQ and implicit learning is that different implicit learning paradigms are only weakly correlated with one other (Gebauer & Mackintosh, 2007, in preparation; Pretz, Totz, & Kaufman, 2010; Salthouse et al., 1999) and may differ in the extent to which they are measuring implicit learning without relying on explicit processes (e.g., Seger, 1994).

Direct comparisons of implicit and explicit versions of specific tasks may further help to explain contradictory results. In some studies, researchers administered the same implicit learning task under two conditions: in one condition, participants were explicitly instructed to detect the underlying covariation, and in the other condition participants did not receive such an instruction, thereby making learning 'incidental' to the task requirements. In these studies, psychometric intelligence was more highly correlated with the task under explicit instructions than under incidental conditions (Unsworth and Engle, 2005a; Gebauer & Mackintosh, 2007). Similarly, in study of 455 adolescents, Feldman et al. (1995) separated an intentional declarative component of an implicit learning task from the procedural component and found that, although the declarative learning component significantly correlated with psychometric intelligence, the procedural component did not. Overall it appears that individual differences in psychometric intelligence, which are clearly associated with variation in explicit cognition, are either weakly or not at all associated with variation in implicit learning (e.g. McGeorge et al., 1997; Reber et al., 1991).

While implicit learning is only weakly related to psychometric intelligence, recent research suggests that individual differences in implicit learning may make an independent contribution to complex cognition. Gebauer and Mackintosh (in preparation) administered a battery of 15 traditional implicit learning tasks and nine traditional psychometric intelligence tests to 195 German school pupils. Factor analyses revealed a low correlation between two second-order principal components, the first corresponding to psychometric intelligence and the second corresponding to implicit learning. In addition, their second-order factor of implicit learning correlated significantly with school grades in Math and English (a foreign language for the German participants in the study). Controlling for psychometric intelligence, the correlation between the implicit learning factor and English grades remained, while the relation to Math was no longer significant. Similarly, Pretz et al. (2010) found a significant relation between a measure of serial reaction time (SRT) probabilistic learning and Math and English achievement scores. These results suggest there may be variance in implicit learning ability that is independent of psychometric intelligence but nevertheless related to some aspects of school learning.

A number of basic cognitive mechanisms, including working memory, explicit associative learning, and processing speed, have been posited as contributors to intelligence (e.g., Kaufman, DeYoung, Gray, Brown, & Mackintosh, 2009). Examining their relations to implicit learning may help to clarify the relation of implicit learning to other aspects of cognition. Below we review the available evidence on the relation of these cognitive mechanisms to implicit learning.

1.1. Implicit learning and working memory/executive attention

Working memory is defined as the ability to maintain, update, and manipulate information in an active state, over short delays. It depends heavily on executive attention; those with a high working memory are better able to control their attention, maintaining task goals in the presence of interference (Conway, Cowan, & Bunting, 2001; Kane, Bleckley, Conway, & Engle, 2001; Unsworth, Schrock, & Engle, 2004). Over the last two decades, considerable debate has arisen over the question of whether implicit learning, like working memory, depends on the executive functions of attention, or whether it arises automatically as a by-product of processing a set of correlated events (Jiménez, 2003; Shanks, 2003). Much experimental work (e.g., Baker, Olson, & Behrmann, 2004; Frensch & Miner, 1995; Jiang & Chun, 2001; Jiménez & Mendez, 1999; Turke-Browne, Junge, & Scholl, 2005) appears to be converging on the conclusion that, for implicit learning to occur, selective attention to the relevant stimuli is required. However, learning about the stimuli that are selectively attended to then occurs automatically, regardless of an intention to learn, and without necessitating any further executive processing resources.

One implication of this conclusion is that central executive resources should be engaged under explicit learning instructions, to guide the focus of attention, whereas only selection processes should be required for incidental learning (Cowan, 1988, 1995; Frensch & Miner, 1995; Johnson & Hirst, 1993). Working within this framework, Unsworth and Engle (2005) demonstrated that working memory differences emerge in an implicit learning task under explicit instructions to detect the covariation, but not under incidental conditions where no such instructions were given. Similarly, Feldman et al. (1995) found nonsignificant correlations between implicit learning and measures of working memory.

In sum, the available data suggest that implicit learning operates in an automatic fashion once relatively low-level perceptual attention is selectively allocated to the appropriate stimuli, without necessarily requiring executive attention. This leads us to hypothesize that individual differences in implicit learning are not associated with individual differences in working memory.

1.2. Implicit learning and explicit associative learning

Associative learning, as conceived in the implicit learning literature, differs from the type of associative learning typically discussed in the intelligence literature (e.g., Underwood, Boruch, & Malmi, 1978; Williams & Pearlberg, 2006). In the implicit learning literature, learning is often termed as associative (as opposed to cognitive), when learning proceeds incidentally, because it describes the incidental formation of associations. Connectionist modeling based on this assumption has successfully modeled many aspects of implicit learning (e.g., Cleeremans, 1993; Cleeremans & Dienes, 2008). By contrast, in the intelligence literature, associative learning is often used to describe the learning of associations acquired consciously and intentionally according to explicit instruction and feedback. To date, no study has investigated the relationship between implicit learning and explicit associative learning. Although prior studies have ostensibly compared explicit and implicit learning (e.g., Reber et al., 1991), measures of "explicit learning" in these studies have typically been measures of explicit reasoning, such as series completion, that do not, in fact, require learning over the course of the experiment. Despite the fact that both implicit learning and explicit associative learning must involve the formation of associations, we hypothesized that they are unrelated as abilities, for the same reasons that working memory seems likely to be unrelated to implicit learning: executive attention should be required only when learning is intentional.

1.3. Implicit learning and processing speed

Processing speed involves the speed at which very simple operations can be performed. Differences in intelligence may partly reflect the overall efficiency and speed of the nervous system (Anderson, 1992; Jensen, 1998), in addition to more specific capabilities like working memory (Kaufman et al., 2009). Given the primitive and broad nature of processing speed as a parameter, one might expect it to be related to individual differences in implicit learning, even in the absence of implicit learning's association with more complex cognitive mechanisms. Accordingly, Salthouse et al. (1999) found a significant relation between two processing speed measures and implicit learning. One of these measures was the Digit-Symbol Coding test, part of the standard WAIS battery for IQ. Although the factor structure of the WAIS indicates a processing speed factor as one of four second-level factors below *g*, the processing speed tests load on *g* more weakly than other types of test (Deary, 2001). We therefore expected that, although implicit learning may be only weakly or not at all related to *g*, it may show a significant relation to processing speed.

1.3.1. Implicit learning and personality

Research on the personality correlates of implicit learning is limited. However, theoretical links between implicit learning and intuition allowed us, in conjunction with the available evidence, to make predictions regarding personality traits reflecting an intuitive cognitive style, especially those related to the Big Five trait domain of Openness/Intellect and to impulsivity.

1.3.1.1. Intuition. Implicit learning and intuition are closely related constructs. Indeed, it has been argued that intuition is the subjective experience associated with the accumulated knowledge gained through an implicit learning experience (Dienes, 2008; Lieberman, 2000; Reber, 1989). Reber (1989) further explains how implicit learning and intuition can be related:

> To have an intuitive sense of what is right and proper, to have a vague feeling of the goal of an extended process of thought, to "get the point" without really being able to verbalise what it is that one has gotten, is to have gone through an implicit learning experience and have built up the requisite representative knowledge base to allow for such a judgement (p. 233).

Woolhouse and Bayne (2000) looked at the relation between personality as measured by the Myers-Briggs Type Indicator (MBTI) (Myers, McCaulley, Quenk, & Hammer, 1998), and performance on a hidden covariance detection task (Lewicki, Hill, & Sasaki, 1989), in which participants implicitly learned to judge the job suitability of job applicant personality profiles based on the covariance between personality profiles and information about job suitability in the training phase. A test phase with new profiles showed that participants learned the covariation regardless of whether they were explicitly aware of the rules. Individual differences emerged, however, when considering task performance along the MBTI dimension of intuition/sensation, which was designed to measure the extent to which people prefer to make decisions using factual, simple, and conventional methods (sensation) vs. a preference for the possible, complex, and original (intuition) (McCrae, 1994). Sensation types were more likely to be consciously aware of the covariation and apply it effectively. Among those who lacked awareness of the underlying rule, however, there was a tendency for participants with a more intuitive personality to make greater and more accurate use of their intuition on the implicit learning task. These authors concluded that personality influences whether people will use intuition based on implicit knowledge to help them arrive at a correct answer in the absence of explicit knowledge.

1.3.1.2. Openness/Intellect. The five factor model or Big Five is the most widely used and best validated taxonomy of personality traits (Goldberg, 1990; Markon, Krueger, & Watson, 2005). Within the Big Five, the MBTI dimension of sensing-intuition falls within the domain of Openness/Intellect (McCrae, 1994). The compound label for this dimension reflects an old debate about how best to characterize this personality factor, with some researchers favoring the label "Intellect" (e.g., Goldberg, 1990) and others favoring "Openness to Experience" (e.g., Costa & McCrae, 1992). This debate has been largely resolved by the recognition that Openness and Intellect reflect separable but related aspects of the larger domain (Johnson, 1994; Saucier, 1992). This distinction was recently given more empirical support by the finding of two correlated factors within 15 scales measuring different lower-level facets of Openness/Intellect (DeYoung, Quilty, & Peterson, 2007). The two factors were clearly recognizable as Intellect and Openness, with Intellect reflecting a combination of perceived cognitive ability and tendency toward intellectual engagement, and Openness reflecting artistic and contemplative qualities and engagement with sensory and perceptual information. The analysis of DeYoung et al. (2007) generated new scales to measure Openness and Intellect separately and also demonstrated that different subscales of the NEO PI-R Openness to Experience scale (Costa & McCrae, 1992) could be used as markers of Openness and Intellect. McCrae (1994) found that the MBTI intuition scale was more strongly related to Openness than to Intellect, at the facet level.

Based on the link between Openness and intuition, we hypothesized that scales loading on Openness would be positively associated with implicit learning. Scales related to Intellect, in contrast, appear to be more closely linked to intelligence, working memory, and explicit associative learning (DeYoung, Peterson, & Higgins, 2005; DeYoung, Shamosh, Green, Braver, & Gray, 2009). We hypothesized that they would be associated with these other cognitive abilities, but not with implicit learning.

1.3.1.3. Impulsivity. In recent years, dual-process theories of reasoning have become increasingly required for explaining cognitive, personality, and social processes (see Evans & Frankish, 2009). Although the precise specifications of the theories differ, most have in common the idea that humans possess both automatic and controlled processes that jointly contribute to behavior. This idea has recently been elaborated on by Strack and Deutsch (2004) who argue that behavior is multiply determined by both impulsive and reflective processes.

Prior research shows that impulsivity is negatively related to both *g* and working memory (Kuntsi et al., 2004; Shamosh & Gray, 2007; Shamosh et al., 2008). Here we investigate the relation between implicit learning and impulsivity. According to Strack and Deutsch (2004), the impulsive system involves an associative network that is automatically activated through learning and experience. They argue that "structures emerge in the impulsive system that bind together frequently co-occurring features and form associative clusters (p. 223)." They further state that "the impulsive system has low flexibility but is fast and needs no attentional resources" (p. 224). This characterization strongly suggests that implicit learning ability might be positively associated with trait impulsivity.

Whiteside and Lynam (2001) identified four major dimensions of variance pertaining to impulsivity: urgency, lack of premeditation, lack of perseverance, and sensation seeking. We hypothesized that the most relevant form of impulsivity for implicit learning is lack of premeditation, in that individuals who deliberate extensively may do so in part because they are poor at detecting incidental covariances and therefore have reduced access to quick and intuitive decisions.

2. The present study

To investigate the cognitive and personality correlates of individual differences in implicit learning we used what we believe to be the best measure of implicit learning currently available (see Section 3). In line with the prior literature just reviewed, our hypotheses regarding the pattern of relations to implicit learning are as follows:

> *Hypothesis 1.* Psychometric intelligence is correlated more strongly with explicit associative learning than with implicit learning.

Hypothesis 2. Implicit learning is not related to working memory, or explicit associative learning, but is related to processing speed. Implicit learning is also related to other measures of cognitive performance independently of psychometric intelligence and the elementary cognitive tasks associated with psychometric intelligence.

To assess these two hypotheses, we examined zero-order correlations between individual differences in implicit learning and tests of these other cognitive variables, including tests of academic achievement. Then we assessed the association of latent cognitive constructs with implicit learning.

Hypothesis 3. Implicit learning is significantly associated with Openness and the related trait of Intuition but is not associated with Intellect. Further, there is a double dissociation, with Intellect related to working memory (DeYoung et al., 2005, 2009) and Openness related to implicit learning.

To assess this hypothesis, we examined zero-order correlations between implicit learning and markers of Openness and Intellect, including MBTI Intuition, as well as correlations of implicit learning with latent Openness and Intellect variables. To test the double dissociation, we created a structural model using Intellect and Openness as simultaneous predictors of implicit learning and working memory.

Hypothesis 4. Impulsivity—and particularly lack of premeditation—is positively correlated with implicit learning.

To assess this hypothesis, we examined zero-order correlations between implicit learning and the four impulsivity dimensions identified by Whiteside and Lynam (2001).

3. Method

3.1. Participants

The 153 participants (47 males and 106 females) included in the analysis were aged 16–18 years (Mean = 16.9, SD = .65), and attended a selective sixth form college (which takes high-achieving students who are in their last 2 years of secondary education) in Cambridge, England. Data were collected for 27 other participants, but 24 of these were removed from the analysis because they were missing implicit learning scores, 2 were removed because their Raven Advanced Progressive Matrices scores were below chance, and 1 participant was removed due to obvious lack of effort (e.g., frequent chatting). 147 participants completed all three testing sessions. Due to computer errors and time constraints, not all participants completed all the tests. Where possible, we imputed missing values (see below). A subset of this sample was also analyzed in an examination of the relation of elementary cognitive abilities to intelligence (Kaufman et al., 2009). Those analyses did not include implicit learning or personality questionnaires.

3.2. Procedure

Tests were administered in groups at PC desktop terminals during the course of three 1.5-h sessions. Tests were presented to participants in the same fixed order. As far as possible, all participants received all tests in the same order. Participants earned £20 for their participation in all three testing sessions.

3.2.1. Implicit learning

3.2.1.1. Serial reaction time (SRT) learning. To investigate our hypotheses relating to implicit learning, we focused on a probabilistic version of the serial reaction time task (SRT)—an implicit learning task that the evidence indicates to be the best measure of implicit learning currently available. According to Shanks (2005), the SRT task and the Artificial Grammar learning tasks have become the paradigmatic methods of studying implicit learning. There are reasons to believe, however, that the SRT task is the better measure of implicit learning (Destrebecqz & Cleeremans, 2001). First, sequence learning in the SRT task is more incidental than in Artificial Grammar Learning: learning in the SRT task is an incidental result of responding to stimuli without any instructions to memorize the series or look for underlying rules, whereas, in Artificial Grammar Learning, participants are explicitly told to memorize strings. Second, in Artificial Grammar Learning, there is an explicit separation between the acquisition and test phases: in the test phases, participants are typically informed about the existence of a structure, and are told to try to exploit it. In contrast, the expression of sequence learning in SRT can be measured using reaction time, without telling the participants that there exist both sequence and control trials. This makes the probabilistic SRT task an excellent paradigm to use to minimize the impact of explicit sequence knowledge (Stefaniak, Willems, Adam, & Meulemans, 2008).

The probabilistic version of the SRT task is particularly appropriate because the control trials are interspersed with sequence trials in every block, and learning can thus be measured online (i.e., during the training phase). Further, interspersing structured with control trials has the dual advantages of making it more difficult for participants to explicitly discover the existence of a sequence and of making the task more ecologically valid: implicit learning in the real world often happens under conditions of uncertainty, where information to be learned is noisy and probabilistic instead of deterministic (Jiménez & Vázquez, 2005).

In the SRT task, participants saw a stimulus appear at one of four locations on the computer screen, and their task was to press the corresponding key as fast and as accurately as possible. Unknown to the participants, the sequence of successive stimuli followed a repeating sequence intermixed 15% of the time with an alternate sequence (Schvaneveldt & Gómez, 1998). In particular, Sequence A (1–2–1–4–3–2–4–1–3–4–2–3) occurred with a probability of 0.85, and Sequence B (3–2–3–4–1–2–4–3–1–4–2–1) occurred with a probability of 0.15. Fig. 1 shows a representation of this procedure.

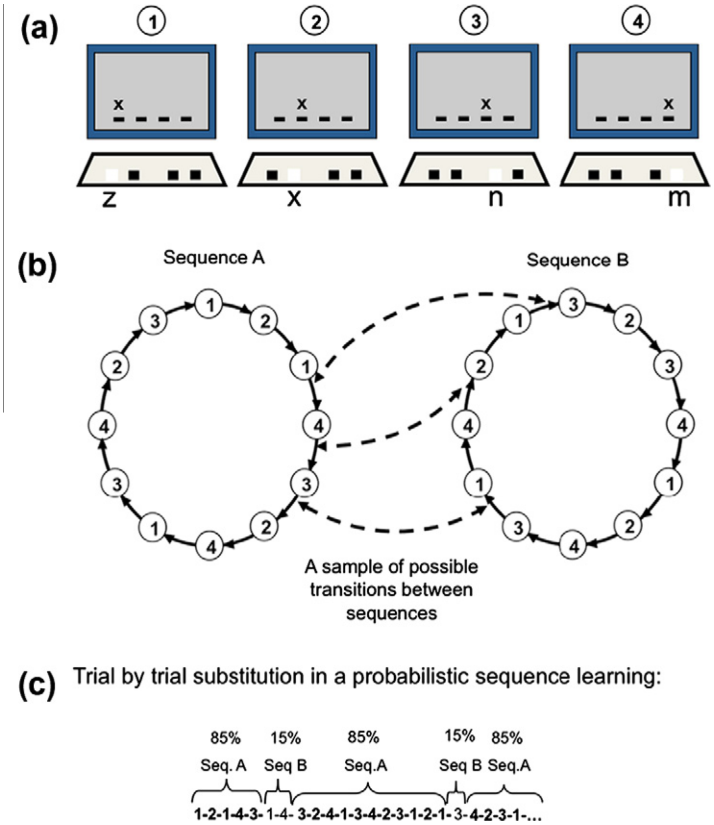

Fig. 1. Structure of a probabilistic sequence learning procedure. *Note*. (a) Representation of the stimulus and the required key-presses for trial types 1, 2, 3, and 4, respectively. (b) Representation of the two 12-trial sequences used to generate either training or control trials for different participants (Sequences A and B). Both sequences are represented as recurrent structures to highlight that the sequences are continuously recycled, and that the starting point is randomly chosen on each block. A sample of possible transitions between sequences is also represented to illustrate that these transitions respect the second-order conditionals of the upcoming sequence. For instance, if a participant is trained with Sequence A and a control trial is scheduled to appear after the series 2–1–4, then the next trial would appear at location 2, which is the successor of the series 1–4 according to Sequence B. (c) Representation of the "trial by trial" substitution procedures employed in these probabilistic sequence learning tasks. Individual trials obeying either the training or the control conditionals are interspersed with each other in a way that respects the transitions between trials as well as the overall likelihood of each type of trial (e.g., 85% of training vs. 15% of control trials). Notice that most trials obeying the unlikely control sequence would appear isolated, but small groups of control trials are also possible.

Note that these two sequences have been built to differ exclusively in the second-order conditional information that they convey (Reed & Johnson, 1994). Thus, each location appears with the same likelihood in each of these two structures, and each first-order transition is also equally likely in both sequences. However, second-order information leads to a different prediction for each sequence, so that learning about this second-order conditional information will lead to a difference in responding to each sequence.

To elaborate on the probabilistic nature of the design: on each trial, the successor could follow either Sequence A or Sequence B. For example, the most common successor in Sequence A after 1–2 was 1, but on some trials (15% of the time) the successor was instead 4, as stipulated by Sequence B after the context 1–2. After this substitution, the context would be 2–4, and hence the most common successor (85% of the time) was the usual location marked by Sequence A to appear in this context (1). However, there was a certain probability (15%) that the successor marked by Sequence B (3) could occur.

During the practice block (0), probable and improbable transitions occurred with equal likelihood. Thus, the next trial in sequence was equally likely to be determined by Sequence A as by Sequence B. After this practice block, participants completed eight training blocks in which transitions were generated from Sequence A 85% of the time and from Sequence B 15% of the trials. Participants completed 120 trials in each block, 960 trials in total. Within each block, all trials were initially randomized but then presented in the same fixed order for each participant. This was done to maximize the extent to which individual differences reflect trait differences rather than differences in item order.

As noted above, there are reasons to believe that this probabilistic version of the SRT is an excellent measure of implicit learning (Jiménez & Vázquez, 2005). For one, the probabilistic version does not contain any first order information that could account for learning, because after each location any other is equally probable. Secondly, the probabilistic nature of the task minimizes the effect of chunk learning, and instead maximizes the need to learn the conditional probabilities of each successor in each context. During post-experiment interviews, no participants indicated knowledge that the transitions were probabilistic or conditional on the two previous locations.

To assess learning on the probabilistic SRT task for each participant, we first took the difference between the average time to respond to probable trials and the average time to respond to improbable trials. Error responses were discarded (3.5% of trials), as well as outliers more than three standard deviations from the mean, which were computed individually for each block and participant. On average, 2% of the trials qualified as outliers according to these criteria.

When investigating individual differences, it has been assumed that a simple RT-difference learning score, like the one just described, can be used to provide a rank ordering of ability to learn on the SRT. However, this assumption may be flawed because the exact difference in RT may not be stable enough to provide a reliable rank order. More important than the exact RT difference between probable and improbable trials may be simply whether or not individuals show any reliable difference between RTs to probable and improbable trials. For this reason, we investigated a new scoring method based on a binary index of whether participants showed learning in each block.

The crucial statistic to consider before adopting this new method is its reliability. When measuring variables that may qualify as traits (that is, relatively stable individual differences), a key index of a measure's reliability is its internal consistency (that is, the rank-order stability of individuals' scores on different items or sections of the measure). Unreliability attenuates the effect size of associations between measures. The less reliable is a measure of some trait, the lower its possible observed correlation with another variable can be, regardless of the true correlation between that trait and the other variable. Behavioral tasks, like SRT, often show relatively low reliabilities, and any increment in reliability that can be achieved is an important step toward successfully measuring individual differences in implicit learning.

For the new SRT scoring method, rather than calculate an exact RT difference, we simply assessed whether participants showed a learning effect at least as large as the learning effect evident in the sample as a whole, across blocks 3–8 (blocks 1 and 2 were not included because learning was not clearly established in the sample as a whole until block 3; see Section 4 for details). The global effect size for the sample was used because it provided a non-arbitrary criterion for learning. The average Cohen's d for probable vs. improbable trials across these blocks was .19. Because the average difference between the conditions across these blocks was .19 standard deviations, we assessed for each participant in each block of learning whether their mean RT for probable trials was less than the difference between their mean RT for improbable trials and .19 times their standard deviation for RT on improbable trials. If it was less, they received a score of 1. If it was not, they received a score of 0. To calculate a total score for each participant, we summed their score across the last six blocks, yielding a minimum score of 0 and a maximum score of 6.

The new scoring method demonstrated an acceptable split-half reliability (using Spearman–Brown correction) of .44, and the distribution was normal. This level of reliability is similar to the reliability of implicit learning previously reported in the literature (Reber et al., 1991; Dienes, 1992). The old scoring method relying on RT differences demonstrated a split-half reliability of only .33, for the same six blocks. Therefore, all results are presented utilizing the new scoring method. The correlation between RT difference scores and scores from the new method was .76, and a side by side comparison of correlations using the old and new scoring methods showed a similar pattern in the direction of correlations, but with consistently stronger effects using the new, more reliable scoring method. This is what one would expect, given that lower reliability leads to greater attenuation of correlations. Further, a recently published study (Pretz et al., 2010) used the same probabilistic SRT task in an undergraduate sample, and also adopted the same novel scoring method, and found significant correlations with tests of Math and English achievement. Thus, the method has proved effective in multiple, demographically different samples.

3.2.2. Psychometric intelligence

To create a representative latent g factor we used one verbal test, one perceptual reasoning test, and one mental rotation test. Using one of the largest batteries of cognitive tests ever collected, Johnson and Bouchard (2005) demonstrated that, below the g factor, there are three separable second-stratum domains of cognitive ability: verbal, perceptual, and mental rotation. Therefore, use of one test from each domain should produce a well-balanced g.

3.2.2.1. Raven's advanced progressive matrices test, set II (Ravens). Ravens (Raven, Raven, & Court, 1998) is a measure of abstract perceptual reasoning. Each item consists of a 3×3 matrix of geometric patterns with the bottom right pattern missing. The participants' task is to select the option that correctly completes the matrix. There are eight alternative answers for each item. The test is presented in increasing order of difficulty. After two practice items with feedback, participants were then given 45 min to complete 36 items.

3.2.2.2. DAT verbal reasoning test. The verbal reasoning section of the Differential Aptitudes Test (DAT-V, The Psychological Corporation, 1995) was administered to each participant. Each problem consisted of a sentence with two words missing, and participants chose a pair of words from the answer options that were analogically related to the words in the sentence. After two practice items, participants had 15 min to complete 40 problems.

3.2.2.3. Mental rotations test, set A (MRT-A). The MRT-A (Vandenberg & Kruse, 1978) contains 24 problems and measures mental rotation ability, and appears to be a distinct component of intelligence to the same extent as verbal ability and perceptual ability (Johnson & Bouchard, 2005). Each problem in the MRT-A shows a three-dimensional target figure paired with four choice figures, two of which are rotated versions of the target figure. To score

Table 1
Correlations among all measures of *g*, elementary cognitive tasks, implicit learning, Intellect, Openness, Intuition, and Impulsivity.

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1. Ravens	–																							
2. DAT Verbal reasoning test	.50	–																						
3. Mental rotations test	.58	.41	–																					
4. Operation span task	.34	.44	.27	–																				
5. Verbal speed test	.22	.22	.17	.23	–																			
6. Figural speed test	.26	.12	.16	.10	.23	–																		
7. Numerical speed test	.25	.10	.21	.12	.14	.56	–																	
8. Three - Term Contingency Learning	.31	.37	.23	.20	.14	.19	.04	–																
9. Paired - associates learning	.27	.25	.14	.11	.23	.20	−.04	.67	–															
10. Implicit learning	.13	.22	.05	.05	.00	.25	.12	.05	.06	–														
11. BFAS Intellect	.32	.41	.30	.27	.16	.17	.06	.24	.11	.07	–													
12. BFAS Openness	.12	.29	.06	.19	.04	.22	.11	.14	.06	.29	.19	–												
13.NEO Fantasy	.19	.21	.14	.22	−.02	.11	.02	.17	.06	.16	.18	.47	–											
14. NEO Aesthetics	.10	.20	−.04	.11	.08	.24	.20	.12	.03	.21	.28	.72	.36	–										
15. NEO Feeling	.06	.13	.05	.16	.05	.20	.11	.20	.13	.14	.21	.50	.36	.49	–									
16. NEO Action	.06	.11	.02	.13	−.03	.26	.13	.05	.01	.14	.22	.38	.18	.37	.38	–								
17. NEO Ideas	.42	.37	.30	.26	.12	.27	.18	.30	.13	.13	.71	.34	.31	.47	.33	.27	–							
18. NEO Values	.12	.24	.15	.17	.14	.15	−.04	.07	.02	.12	.21	.29	.20	.20	.22	.26	.19	–						
19. MBTI Intuition	.16	.24	.12	.17	−.02	.14	.07	.12	−.06	.25	.17	.45	.39	.36	.16	.25	.34	.13	–					
20. REI Rational Favorability	.40	.31	.28	.27	.06	.20	.10	.24	.15	.16	.70	.20	.22	.27	.28	.23	.79	.22	.26	–				
21. UPPS Premeditation	.00	−.09	.05	−.14	.09	.04	.02	.07	.07	−.23	.08	−.29	−.36	−.14	−.16	−.36	.05	−.19	−.32	.06	–			
22. UPPS Urgency	−.08	−.02	−.01	.17	.07	−.10	−.07	.07	.04	.02	−.15	.20	.17	.14	.20	.05	−.09	−.01	.05	−.20	−.38	–		
23. UPPS Sensation seeking	.02	.05	.23	.02	−.03	.23	.34	−.02	−.01	.16	.05	.17	.07	.23	.15	.40	.04	.02	.13	−.12	−.28	.08	–	
24. UPPS Perseverance	.00	−.07	−.07	−.13	.03	.19	.07	.02	.13	−.06	.24	−.20	−.24	−.01	−.01	.01	.13	−.14	−.16	.26	.44	−.41	−.03	–
N	153	153	153	153	147	147	147	147	147	153	145	145	145	145	145	145	145	145	145	146	144	144	144	144
Mean	21.8	24.4	13.2	43.9	40.9	64.4	30.9	42.6	56.2	3.1	3.6	3.8	3.9	3.4	3.8	3.1	3.5	3.9	18.7	3.6	3.2	3.3	3.7	3.2
SD	5.2	5.9	5.3	8.5	9.3	10.2	4.3	21.4	19.2	1.5	.60	.60	.65	.82	.62	.54	.70	.49	5.2	.65	.65	.63	.68	.72
Reliability	.80	.79	.78	.72	.65	.65	.65	.93	.96	.44	.78	.73	.78	.80	.77	.60	.80	.62	.84	.84	.87	.82	.84	.87

Note. Correlations > .16 in absolute value are significant at $p < .05$.

a point, both rotated versions must be identified. After two practice items with feedback and an explanation, the first 12 problems were attempted in 4 min with a 2 min break before attempting the second 12 in another 4 min. The maximum score is 24.

Mean scores on the three cognitive ability measures (Ravens, DAT-V, and MRT-A) suggested a mean IQ for the entire sample in the range of 100–110 (see Table 1).

3.2.3. Elementary cognitive tasks

3.2.3.1. Operation span task (Turner & Engle, 1989). The Operation Span (Ospan) was used as our measure of working memory. Ospan is one of the most well validated and widely administered measures of working memory available in the literature (Unsworth & Engle, 2005b). Additionally, prior research has demonstrated significant correlations between Operation Span and *g* (e.g., Unsworth and Engle, 2005b).

Ospan requires participants to store a series of unrelated words in memory while simultaneously solving a series of simple math operations, such as "Is $(9/3) - 1 = 1$?". After participants selected the answer, they were presented with a word (e.g., DOG) to recall. Then participants moved onto the next operation-word string. This procedure was repeated until the end of a set, which varied from two to six items in length. Participants were then prompted to recall all the words from the past set in the same order in which they were presented by typing each word into a box, and using the up and down arrow keys on the keyboard to cycle through the boxes.

Before the test phase, participants encountered three practice problems with set size two, where they received feedback about their performance. During these practice trials, we calculated for each participant how long it took them to solve the math operations. Consistent with the methodology of the Automated Ospan task (Unsworth et al., 2005), we did this to control for individual differences in the time required to solve the math operations. Their mean performance time to solve the equations, plus 2.5SD was used as the time limit for the presentation of the math equations during the main task.

The Ospan score is the sum of all correctly recalled words in their correct positions. The number of operation word-pairs in a set was varied between two, three, four, five, and six with three sets of each. Overall score could range from 0 to 60.

3.3. Explicit associative learning tasks

For both explicit associative learning tasks, all stimuli were initially randomized but then presented in the same fixed order for each participant. This was done to maximize the extent to which individual differences reflect trait differences rather than differences in item order.

Three-Term Contingency Learning (Williams & Pearlberg, 2006). The Three-Term Contingency Learning (3-Term) task consists of four learning blocks, each followed immediately by a test block. In each learning block, participants were presented with 10 unique words. Each word was associated with three different words, contingent on a key press. The participants' task was to learn the word associated with each stimulus–response pair. For instance, on one trial the word "LAB" might show on the screen with the letters "A", "B", and "C" listed underneath. When participants selected "A", they saw one association (e.g., PUN), when they selected "B", they saw a second association (e.g., TRY), and when they selected "C" they saw a third association (e.g., EGG). The duration of exposure to each association was self-paced (max 2.5 s) with change-over intervals set at 0.2 s. After the single presentation of all 10 stimulus words with the 30 outcome words, subjects were immediately presented with a test block.

The test blocks were identical to the learning blocks with one exception: instead of typing the letters "A", "B", or "C" to produce the outcome words on the screen, a stimulus word appeared on the screen along with one of "A", "B", or "C", and participants were required to type in the outcome word corresponding to that stimulus–response pair. Together with feedback on their answer, the correct association was shown to the participants until they pressed "ENTER", when the next stimulus word was presented. Once the test block was completed, participants immediately moved to a second learning block in which the same stimulus words were presented in a different order. Across the four test blocks, possible overall scores ranged from 0 to 120.

Paired-associates (*PA*) *learning* (Williams & Pearlberg, 2006). In this task, participants were presented with 30 pairs of words. A cue word was presented until the participant pressed ENTER, or until 2.5 s elapsed, after which the cue's pair appeared on the screen. They then remained together on screen, again until the participant pressed ENTER, or until 2.5 s elapsed, after which both disappeared and the next cue word was displayed. The test phase was identical to training, except instead of pressing "ENTER" to view the second word of each pair subjects were required to type that word. Together with feedback on their answer, the correct association was shown to the participant until they pressed "ENTER", when the next word cue was presented. Once the test phase was completed, participants immediately moved to a second learning block in which the same stimulus words were presented in a different order. In total, there were four learning and four test blocks, with possible overall scores ranging from 0 to 120.

3.4. Processing speed tests

Verbal speed test (*Speed-V*): an English adaptation of a sub-test from the Berlin model of Intelligence Structure (BIS; Jaeger, 1982, 1984). The task was to fill in the missing letter from a 7-letter word; 60 s were given to complete the 57 items. The score is the number completed correctly in 60 s.

Numerical speed test (*Speed-N*): the Speed of Information Processing sub-test from the British Ability Scales (Elliot, 1996). The task was to cross out the highest number in each row of five numbers; 60 s were given to complete 48 items. The score is the number completed correctly in 60 s.

Figural speed test (*Speed-F*): Digit-Symbol Coding, a sub-test of the WAIS-R that loads on the "processing speed" factor (Deary, 2001). The test was to enter the appropriate symbol (given by a key at the top of the form) beneath a random series of digits; 90 s were given to complete 93 items. The score is the number completed correctly in 90 s.

3.4.1. Academic achievement

3.4.1.1. General certificate of secondary education (GCSE). The participants in this study reported GCSE scores. GCSE exams are national, subject-based exams taken by students in England between the ages of 15–16 (11th year of schooling) before entry to 6th form and, depending on the subject, involving some combination of coursework and written, listening, speaking, and reading examinations. The year the participants took their GCSE's, GCSE English language, Math, and Science (whether double or single) were compulsory. Although a second language was not compulsory at that time, most schools encourage it, and the requirements vary from school to school. In the school in which the participants took the test, a great majority took such a course, which is consistent with the quality of students at that school.

Based on prior reports of a correlation between implicit learning and Math and language achievement (Gebauer & Mackintosh, in preparation; Pretz et al., 2010), we focused our analysis just on Math and language-related courses.

3.4.2. Personality

3.4.2.1. The Big Five aspect scales (BFAS). The Big Five Aspect Scales (BFAS) assess the personality traits of the five factor model or Big Five (DeYoung et al., 2007). In the BFAS, each of the five major domains is broken down into two subtraits that capture key aspects of the domain. These aspects were derived empirically from factor analysis of facet-level scales from two major Big Five instruments, the NEO PI-R (Costa & McCrae, 1992) and the AB5C-IPIP (Goldberg, 1999). Additionally, the two aspects in each domain appear to correspond to genetic factors found within the facets of the NEO PI-R (Jang, Livesley, Angleitner, Riemann, & Vernon, 2002). In the Big Five domain of Openness/Intellect, not surprisingly, the two aspects clearly reflect Openness and Intellect.

3.4.2.2. NEO-PI-R. The Openness to Experience scale of the NEO-PI-R was administered. The Openness to Experience scale is divided into six subscales or "facets" (descriptions according to Piedmont, 1998): Openness to Aesthetics (deep appreciation for art and beauty), Openness to Action (preference for novelty and variety), Openness to Fantasy (vivid imagination and active fantasy life), Openness to Feelings (receptivity to one's own inner feelings and emotions), Openness to Ideas (active pursuit of intellectual interests for their own sake and a willingness to consider new, perhaps unconventional ideas), and Openness to Values (readiness to reexamine social, political, and religious values). The Aesthetics, Fantasy, Feelings, and Actions facets are good markers of the Openness aspect of the domain, whereas the Ideas facet is a good marker of Intellect (DeYoung et al., 2007).

3.4.2.3. Rational–Experiential Inventory (REI). The Rational–Experiential Inventory (REI) was designed to measure the two different aspects of Epstein's Rational–Experiential model of personality (Epstein, Pacini, & Norris, 1998; Pacini & Epstein, 1999). The REI is a 20-item questionnaire consisting of two subscales—the rational and experiential inventories. The rational inventory attempts to quantify an individual's ability and preference for relying on logic and analysis in making decisions and solving problems. This scale is based on the Need for Cognition Scale (Cacioppo & Petty, 1982), which correlates very highly with the Ideas facet of the NEO PI-R ($r = .78$; Cacioppo, Petty, Feinstein, & Jarvis, 1996). The REI rational favorability subscale was used to provide a third marker of Intellect in analysis with latent variables.

3.4.2.4. The UPPS impulsivity scale. The UPPS Impulsivity Scale was derived from factor analysis of a large number of scales commonly used to measure impulsivity-related constructs (Whiteside & Lynam, 2001). This analysis found four factors, labeled Urgency, (lack of) Premeditation, (lack of) Perseverance, and Sensation Seeking. According to Whiteside, Lynam, Miller, and Reynolds (2005, p. 561), urgency "refers to the tendency to engage in impulsive behaviors under conditions of negative affect despite the potentially harmful longer-term consequences" (lack of) Premeditation "refers to a difficulty in thinking and reflecting on the consequences of an act before engaging in that act" (lack of) Perseverance refers to both "an individual's inability to remain focused on a task that may be boring or difficult", and "difficulty completing projects and working under conditions that require resistance to distracting stimuli", and finally Sensation Seeking reflects "a tendency to enjoy and pursue activities that are exciting and an openness to trying new experiences that may be dangerous."

3.4.2.5. Myers-Briggs Type Indicator (MBTI). The MBTI measures individual differences in personality as a function of four constructs: extraversion/introversion, intuition/sensation, thinking/feeling, and judging/perceiving after Jung's (Jung, 1921/1971) theory of psychological types. The intuition/sensation scale was administered for this study. "Intuitive" individuals are described as concentrating on patterns and possibilities rather than concrete details, whereas a "sensing" person is more concerned with details and facts than an intuitive person. The Intuition scale was scored as a continuous dimension ranging from low (sensation) to high (intuition).

3.5. Missing values

In instances where we could reliably estimate missing values, we did so using expectation–maximization based on scores on other tests measuring the same construct. Data from the other two markers of *g* were used to impute 17 missing Ravens values. For Speed-*F*, six participants did not follow the directions correctly and their scores could not be included in the analysis. Therefore, we used data from the other two markers of processing speed (Speed-*V* and Speed-*N*) to impute missing values on Speed-*F*.

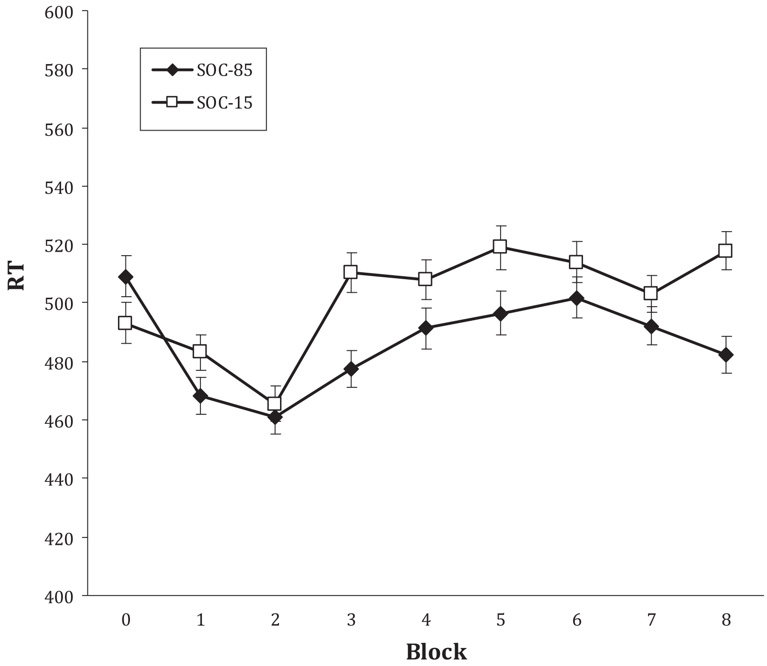

Fig. 2. SRT learning performance for probable (SOC-85) and non-probable (SOC-15) trials across one practice and eight learning blocks ($N = 153$). SOC = second-order conditional.

4. Results

4.1. Validation

We first validated that implicit learning took place on the probabilistic serial reaction time (SRT) learning task. Fig. 2 shows learning on each block at the group level of analysis, comparing mean RT for trials that followed the most probable (85%) sequence with the mean RT for trials that do not follow the most probable sequence (15%).

A repeated-measures analysis of variance (ANOVA) with block (8) and type of trial (2, training vs. control) was conducted on the measures of RT. The results showed a significant effect of block, $F(7, 1064) = 38.77$; $p < .0001$ partial $\eta^2 = .20$, and type of trial, $F(1152) = 328.14$; $p < .0001$, partial $\eta^2 = 0.68$, as well as a significant interaction block $\times$ type of trial, $F(7, 1064) = 19.88$; $p < .0001$, partial $\eta^2 = 0.12$, indicating the acquisition of learning about the training sequence. As is evident from an inspection of Fig. 2, a change in the response trends seems to occur from block 3 onwards, in which RT became slightly slower, but the differences between responding to training and control trials became larger. A comparison of the effect of learning between the first two and the last six blocks of training showed that the difference between responding to training and control trials was significantly larger over the latter blocks $F(1, 152) = 233.51$; $p < .0001$. Further, the average Cohen's d across the last six blocks was .19. We used this average effect as the criterion for our scoring procedure (see Section 3).

Hypothesis 1. Psychometric intelligence is correlated more strongly with explicit associative learning than with implicit learning and implicit learning is not related to working memory, or explicit associative learning, but is related to processing speed.

Table 1 includes all the correlations, descriptive statistics, and reliabilities among all of the variables.

To investigate our first hypothesis, we looked at the zero-order correlations between implicit learning, explicit associative learning, and the three markers of psychometric intelligence. Among the three markers of psychometric intelligence, implicit learning is significantly correlated only with verbal reasoning, $r = .22$, $p < .01$. To assess implicit learning's relation to g and the elementary cognitive task related to g, we constructed latent variables using Amos 7.0 (Arbuckle, 2006), and then analyzed the association among these latent variables and implicit learning. Missing values were estimated by Amos using Maximum Likelihood. A latent variable approach allows for more accurate measurement of the constructs of interest.

The shared variance of Ravens, DAT-V, and MRT-A formed the latent variable representing g. The shared variance of Speed-V, Speed-F, and Speed-N formed the latent variable representing Gs. The shared variance of Ospan trials of set size two, three, four, five, and six formed the latent variable representing WM. The shared variance of blocks 2, 3, and 4 of the 3-Term test phases formed the latent variable "3-Term," and the shared variance of blocks 2, 3, and 4 of the PA test phases formed the latent variable "PA." The latter two latent variables then served as markers for a latent AL variable, with the unstandardized paths from the AL factor to both 3-Term and PA constrained to be equal because two indicators do not provide enough information to determine a unique solution for their loading weights on a latent variable (Kline, 2005).

Correlations among the latent variables and with IL (which was an observed variable) appear in Table 2.

Table 2
Correlations among implicit learning and latent variables for *g* and elementary cognitive tasks.

Measure	1	2	3	4	5
1. *g*	–				
2. Working memory	.55**	–			
3. Processing speed	.38**	.19	–		
4. Explicit learning	.44**	.17	.18*	–	
5. Implicit learning	.16	.06	.24**	.08	–

Note. $N = 153$.
* $p < .05$.
** $p < .01$.

Consistent with our second hypotheses, the only elementary cognitive task to which implicit learning is significantly related is processing speed. Implicit learning is almost entirely uncorrelated with working memory and explicit associative learning. Also in support of our hypotheses, *g* is significantly more strongly correlated with explicit associative learning than with implicit learning, according to a test of equality of correlations (Steiger, 1980), $t(150) = 2.78$, $p < .01$).

The correlation between *g* and IL, however, approaches significance ($p = .08$). To test whether this correlation is due to implicit learning's relation to verbal reasoning, we tested a structural model in which *g*, all elementary cognitive tasks, and verbal reasoning simultaneously predict implicit learning (see Fig. 3).

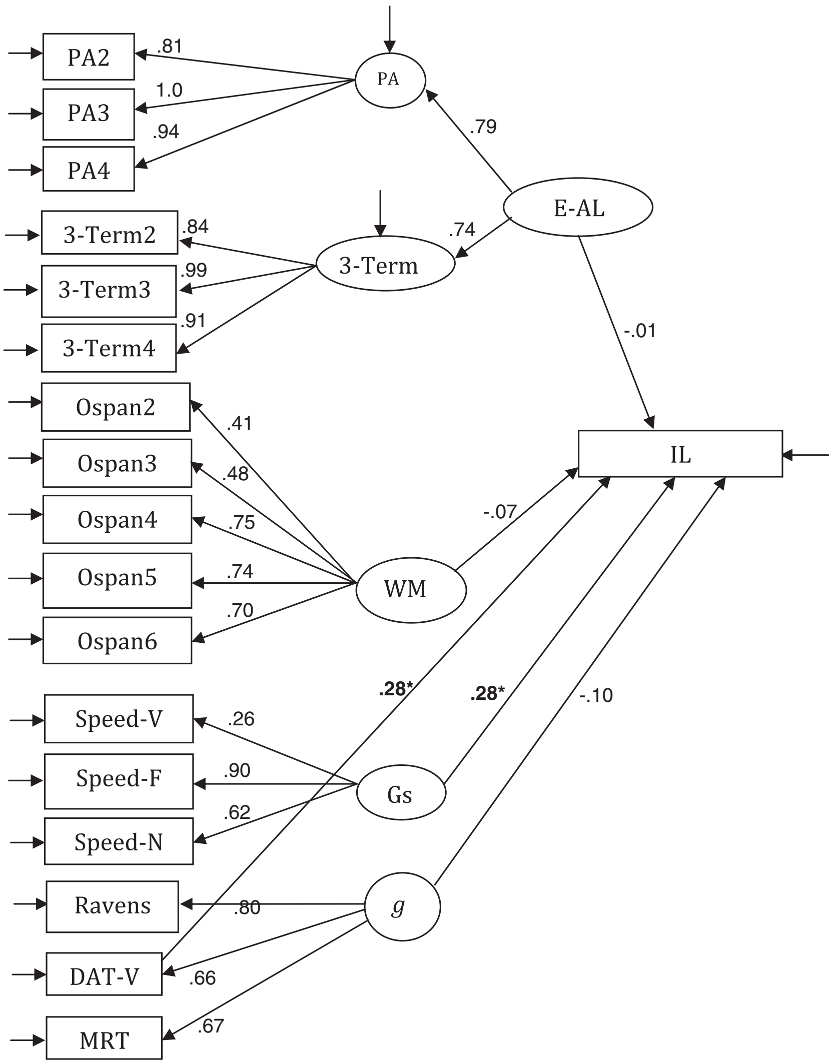

Fig. 3. explicit associative learning (E-AL), working memory (WM), processing speed (Gs), psychometric intelligence (g), and verbal reasoning (DAT-V) predict implicit learning (IL). $N = 153$. $\chi^2 = 189.13$, df = 124, $p < .05$, CFI = .96, TLI = .94, RMSEA = .06, $p_{close} = .19$; $^{*}p < .05$. (All loadings in the measurement model—arrows pointing to the left—are significant.) The latent predictors were allowed to correlate, but these correlations are not shown for clarity of illustration. Key: PA = Paired-associates learning, 3-Term = Three-Term Contingency Learning, Ospan = Operation span task, Speed-V = Verbal speed test, Speed-F = Figural speed test, Speed-N = Numerical speed test, Ravens = Raven's advanced progressive matrices test, DAT-V = DAT verbal reasoning test, MRT = Mental rotations test.

The model was analyzed using Amos 7.0 (Arbuckle, 2006) with maximum likelihood estimation. (The full covariance matrix used to fit the model in Fig. 3 is available from the authors on request.) When all the variables are included together in a structural model, only Processing Speed (Gs) and verbal reasoning (DAT-V) independently predict implicit learning (IL). This suggests that *g*'s zero-order correlation with implicit learning approaches significance only because of verbal reasoning's correlation with implicit learning.[2]

Also listed in Fig. 3 is the χ^2 test for significant discrepancies between the predicted and observed covariance matrices, as well as the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). A significant χ^2 does not necessarily indicate poor fit because the χ^2 value is sensitive to sample size (Kline, 2005). Other fit indices are designed to surmount this limitation. CFI and TLI values over .90 indicate adequate fit and values of .95 or higher indicate close fit (Kline, 2005). RMSEA values less than 0.08 indicate acceptable fit, while values of 0.05 or less indicate close fit (Kline, 2005). The $p_{(close)}$ statistic indicates whether the RMSEA value is significantly greater than 0.05. The fit indices reported in Fig. 3 reveal that the structural model provides a good fit to the data.

Hypothesis 2. Implicit learning is related to other measures of cognition independently of psychometric intelligence and the elementary cognitive tasks associated with psychometric intelligence.

Using only those tests that displayed an adequate *N* for analysis (>40), Table 3 shows the correlations of GCSE Math, English, French, and German scores with *g*, elementary cognitive tasks, and implicit learning.

Implicit learning was significantly correlated with Math and French scores. Although the correlation between implicit learning and German scores was not significant, the effect size (.29) is close to that for the relation between implicit learning and French (.27), suggesting that with a larger sample size the correlation would reach significance. Because *g* and some of the elementary cognitive tasks were also related to these scores, we assessed the partial correlation between implicit learning and the GCSE scores, controlling for *g*, working memory, explicit associative learning, and processing speed. After controlling for these variables, the correlation between Math and implicit learning is no longer significant and the correlation between English and implicit learning is still not significant, but the correlation between implicit learning and French remains significant ($r = .27$, $p < .01$, $N = 102$), and the correlation between implicit learning and German increases to reach significance ($r = .35$, $p < .05$, $N = 42$).

Hypothesis 3. Implicit learning is significantly associated with self-reported Openness and the related trait of Intuition but is not associated with Intellect.

[2] As an even more stringent test of the association of IL with DAT-V independently of *g*, we created a broader *g* variable by allowing the latent E-AL, Gs, and WM variables to load on *g* (instead of merely correlating with *g*). The results remained substantively the same, with DAT-V, but not *g*, significantly predicting IL.

Table 3
Correlations between GCSE scores and *g*, elementary cognitive tasks, and implicit learning.

Measure	GCSE Math	GCSE English	GCSE French	GCSE German
g	.44**	.23*	.22*	.02
Working memory	.26**	.32**	.35**	.14
Processing speed	.32**	.33**	.12	.28
Explicit learning	.16	.20*	.24*	.16
Implicit learning	.21*	.15	.27**	.29
N	145	145	102	42

Note. The *N* for the correlation between Gs and both Math and English is 144. GCSE English scores were calculated by taking the average of GCSE English Language and GCSE English Literature scores. *g* was calculated by assessing the common variance across Ravens, verbal reasoning, and mental rotation using Principal Axis Factoring ($N = 153$). The first PAF accounted for 67% of the total variance in the three tests. Working memory was calculated by summing the Ospan scores for all set sizes. Explicit associative learning was calculated by summing the 3-term and PA learning scores. Processing speed was calculated by summing speed-*F*, speed-*N*, and speed-*F*.
* $p < .05$.
** $p < .01$.

Whereas implicit learning was not related to any of the three markers of Intellect (NEO Ideas, BFAS Intellect, REI Rational Favorability), implicit learning was significantly related to three markers of Openness to Experience (BFAS Openness, NEO Aesthetics, and NEO Fantasy, see Table 1). Consistent with this pattern is the fact that NEO Aesthetics and NEO Fantasy were the two NEO facets that loaded mostly highly on the factor from which the BFAS Openness scale was derived (DeYoung et al., 2007).

Using latent variables for Openness (consisting of BFAS Openness, NEO Aesthetics, NEO Fantasy, NEO Feelings, and NEO Actions) and Intellect (consisting of NEO Ideas, BFAS Intellect, and REI Rational Favorability), Openness was correlated with working memory, processing speed, and implicit learning, and Intellect was associated with *g*, working memory, processing speed, and explicit associative learning, but not implicit learning (see Table 4).

As a consequence of the significant relation of working memory, processing speed, and implicit learning with the latent Openness factor, we ran a structural model to assess the independent effects of implicit learning on Openness, controlling for the other cognitive variables. With *g*, working memory, explicit associative learning, processing

Table 4
Correlations between cognitive tasks, latent variables for Intellect and Openness, and Intuition.

Measure	Intellect	Openness	MBTI Intuition
1. *g*	.55**	.20	.22*
2. Working memory	.35**	.25*	.20*
3. Processing speed	.27*	.30**	.14
4. Explicit learning	.30**	.17	.00
5. Implicit learning	.15	.30**	.25**

Note. $N = 153$ (with estimation for missing values in AMOS).
* $p < .05$.
** $p < .01$.

speed, and implicit learning simultaneously predicting Openness, implicit learning ($\beta = .23$, $p < .01$) remained a significant predictor of the BFAS Openness scale.

Table 4 also shows that *g*, working memory, and implicit learning were significantly correlated with MBTI Intuition. We therefore ran another structural model to assess the independent effects of implicit learning on MBTI Intuition, controlling for the other cognitive variables. With *g*, working memory, explicit associative learning, processing speed, and implicit learning entered simultaneously into a regression model, implicit learning ($\beta = .21$, $p < .05$) remained a significant predictor of the MBTI Intuition scale.

Hypothesis 4. There is a double dissociation, with Intellect related to working memory and Openness related to implicit learning.

The pattern of correlations seen in Table 3 suggest a possible dissociation between Intellect and Openness, with measures of *g* and elementary cognitive tasks associated primarily with an intellectual cognitive style on the one hand, and implicit learning independently associated with openness to experience on the other hand. Openness was associated with working memory at the zero order (Table 3), but this might be due to the variance Openness shares with Intellect, as a previous study did not find any association between Openness and working memory (DeYoung et al., 2009). Because previous studies have suggested that working memory is a key cognitive correlate of Intellect (DeYoung et al., 2005, 2009), we contrasted implicit learning with working memory. To test the double dissociation of Openness and Intellect with implicit learning and working memory, we used structural equation modeling (see Fig. 4). The shared variance of NEO Actions, NEO Aesthetics, NEO Fantasy, NEO Feelings, BFAS Openness, and MBTI Intuition scales formed the latent variable "Openness". The shared variance of the Openness to Ideas facet of the NEO, as well as the BFAS Intellect scale and the REI rational favorability scale formed the latent variable "Intellect". The shared variance of Ospan trials of set size two, three, four, five, and six formed the latent variable "WM". While Openness significantly predicted implicit learning, Intellect did not. Further, while Intellect significantly predicted working memory, Openness did not.

Hypothesis 4. Impulsivity—particularly lack of premeditation—is positively correlated with implicit learning.

Implicit learning was significantly correlated with a lack of premeditation, $r = .23$, $p < .01$, suggesting that there is a tendency for those with higher implicit learning scores to deliberate less about decisions in their daily lives. Also, the relation between implicit learning and sensation seeking was marginally significant, $r = .16$, $p = .05$. Implicit learning was not related to either urgency or perseverance. Intellect was not related to premeditation, urgency, or sensation seeking, but was positively correlated with perseverance, $r = .24$, $p < .05$, suggesting that those higher in Intellect have more self-discipline in their daily lives. Nonetheless, those scoring higher in Intellect do not have higher implicit learning scores (see Table 4).

5. Discussion

The current study conceptualized implicit learning as an ability and assessed the relation of individual differences in implicit learning to psychometric intelligence, elementary cognitive tasks commonly associated with psychometric intelligence, and personality. Contrary to the long-held assumption that individual differences in implicit cognition are minimal relative to individual differences in explicit cognition (e.g., Reber, 1993; Stanovich, 2009), meaningful individual differences in implicit learning were observed. Although unrelated to *g*, intentional

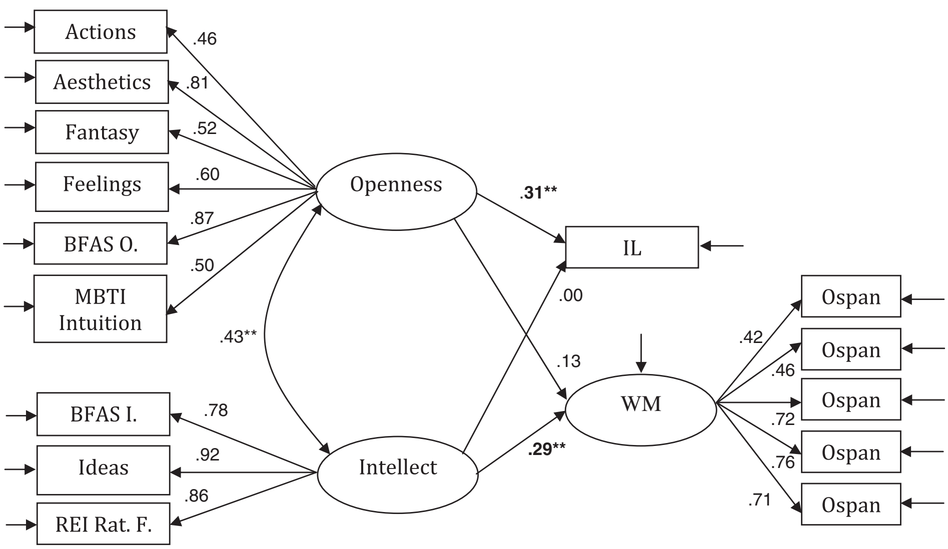

Fig. 4. Double dissociation between Openness and Intellect in predicting working memory (WM) and implicit learning (IL). $N = 153$. $\chi^2 = 118.07$, df = 86, $p < .05$, CFI = .96, TLI = .94, RMSEA = .05, $p_{close} = .50$; $^{**}p < .01$. All loadings of observed variables on latent factors in the measurement model are significant. Key: BFAS O. = BFAS Openness to Experience aspect, BFAS I. = BFAS Intellect aspect, REI Rat. F. = REI Rational Favorability subscale, Ospan = Operation span task.

associative learning, and working memory, implicit learning was independently related to verbal analogical reasoning, processing speed, academic performance, and aspects of self-reported personality. These results have important implications for our understanding of human cognition in general, as they are consistent with dual-process theories of cognition (e.g., Evans & Frankish, 2009) and also suggest independent systems of learning, each with their own sources of individual differences. Below we discuss the important implications of these findings more specifically for the scientific investigation of intelligence, personality, skill learning, complex cognition, and language acquisition.

5.1. Implicit learning, intelligence, and elementary cognitive tasks

The current study found that individual differences in implicit learning were not significantly related to a latent cognitive ability factor indexing *g*. Intentional associative learning was significantly related to *g* and also was significantly more strongly correlated with the three markers of *g* than were individual differences in implicit learning. These findings provide support for Reber's (1989, 1993) hypothesis that individual differences in explicit learning are more related to psychometric intelligence than are individual differences in implicit learning. They are consistent with other empirical data (Gebauer & Mackintosh, 2007; McGeorge et al., 1997; Reber et al., 1991; Feldman et al., 1995), and they are consistent with dual-process accounts of thinking and reasoning (e.g., Evans & Frankish, 2009; Sloman, 1996).

The separation of implicit learning from working memory is consistent with prior reports by McGeorge et al. (1997), Unsworth and Engle (2005a), and Feldman et al. (1995). These studies also lend support to the idea that the explicit and intelligent deployment of cognitive resources in an implicit learning task may be important in the initial stages of the task (in order to attend successfully to the information). However, as long as attention is selectively directed to the relevant stimuli (as in the task by which we measured implicit learning), encoding and access to the incidentally learned structure appears to be no longer dependent on executive attentional resources (Jiménez, 2003; Jiménez & Mendez, 1999; Turke-Browne et al., 2005). It would be interesting for future research to investigate conditions in which individual differences in working memory are predictive of behavior compared to conditions in which individual differences in implicit learning are more predictive of behavior.

Implicit learning was also unrelated to intentional associative learning. This suggests that intentional associative learning may indeed operate through a different cognitive pathway than implicit learning and further supports the distinction between explicit and implicit associative learning. Mackintosh (1998) argued for the existence of a general associative learning system that is largely independent of a cognitive learning system. Since Mackintosh was referring primarily to an implicit, automatic, associative learning system, the current study provides support for his distinction, but also suggests caution in use of the term "associative." One must distinguish between "explicit" and "implicit" associative processes.

Although implicit learning was unrelated to *g*, working memory, and explicit associative learning, implicit learning was significantly associated with processing speed and scores on the verbal reasoning test. A link between implicit learning and processing speed is consistent with prior research (Salthouse et al., 1999) and suggests the possibility that processing speed, like implicit learning, relies in part on mechanisms that are phylogenetically older than the explicit cognitive mechanisms most strongly related to *g*. Future research should further investigate the nature of the link between processing speed and implicit learning. The significant correlation between implicit learning and verbal reasoning scores is more surprising. It represents an association between implicit learning and the residual variance in verbal reasoning not attributable to psychometric intelligence, which suggests that implicit learning may contribute to a more specific language acquisition ability.

The relation of implicit learning to language acquisition is evidenced by the independent association of implicit learning with educational attainment, in particular GCSE French and German results. Educational attainment has long been a yardstick for intelligence research to validate its claim that IQ is related to real-world cognition (Mackintosh, 1998). Moreover, this finding is convergent both with the theoretical assertion that implicit learning is crucial to language acquisition (e.g. Chang, 2008; Ellis, 1994; Karmiloff-Smith, 1992; Perruchet, 2005; Perruchet, 2008; Winter & Reber, 1994) and with empirical findings of an association between measures of implicit learning and language acquisition (e.g. Destrebecqz & Cleeremans, 2008; Gebauer & Mackintosh, in preparation; Gomez, Gerken, & Schvaneveldt, 2000; Krashen, 1992; Pacton, Fayol, & Perruchet, 2005; Pretz et al., 2010; Robinson, 2001; Rohrmeier & Fu, 2008). Further, consistent with the findings of Gebauer and Mackintosh (in preparation), the relation between SRT and second-language acquisition remained significant after controlling for *g*, whereas the relation to Math scores was no longer significant after controlling for *g*. These results suggest that a more complete understanding of language acquisition and perhaps other aspects of cognition could be had by further investigating individual differences in implicit learning.

The results of the current study have implications for intelligence research. Intelligence researchers in the psychometric tradition have predominantly focused on controlled, deliberate reasoning as the hallmark of intelligence (Chabris, 2006; Jensen, 1998; Spearman, 1927). Various researchers have posited additional 'intelligences' (e.g., Gardner, 1993; Sternberg, 1997), which have been criticized on the grounds either that these so-called 'intelligences' are poorly defined and/or measured or that they are not in fact separate intelligences because they are significantly *g*-loaded (Gottfredson, 2003; Visser, Ashton, & Vernon, 2006).

Implicit learning may be related to tacit knowledge, which forms the theoretical core of what Sternberg calls practical intelligence (Wagner & Sternberg, 1986; Sternberg et al., 2000). As Mackintosh (1998) has pointed out, there are striking similarities between Reber's (1989, 1993) description of implicit learning and Wagner and Sternberg's (1986, p. 54) description of tacit knowledge as knowledge that is "not openly expressed or stated...not directly taught..." Indeed, as suggested by Reber (1989), tacit knowledge and intuitive feelings may be the result of an implicit learning experience. It should be noted, however, that in Wagner and Sternberg's conceptualization, tacit knowledge can be either conscious or nonconscious. Furthermore, an analysis of a battery of practical intelligence tests demonstrated that they were, in fact, significantly related to *g* (Cianciolo et al., 2006). Implicit learning ability may come closer to operationalizing the idea of tacit knowledge than any of the "practical intelligence" tests that have been devised, as it seems to be at most only very weakly related to *g*.

5.2. Implicit learning and personality

The current study found that implicit learning was significantly related to the common variance across various self-report measures of the Openness aspect of the Big Five domain Openness/Intellect, as well as to the closely related measure of MBTI Intuition (the latter finding being consistent with results reported by Woolhouse & Bayne, 2000). Implicit learning was not related to the Intellect aspect of the domain, however. Although the causal direction is unclear, these findings do raise the possibility that better unconscious detection and learning of covariance structures may be one of the cognitive mechanisms that support the trait of Openness, as distinct from Intellect. The engagement with the perceptual world that characterizes Openness may be facilitated by implicit learning. Of course, it is also possible that those high in Openness are better at implicit learning because they have a wider focus of attention. Future research could investigate the causal relation between implicit learning and Openness to Experience.

To the best of our knowledge, few other studies have examined the relation between Openness and implicit learning. Norman, Price, and Duff (2006) administered a deterministic SRT task (as opposed to the probabilistic version, like ours, which is thought to be a cleaner measure of implicit learning since it leads to less explicit knowledge of the sequence) and found a significant correlation between Openness to Feelings and the amount of decrease in RT throughout the training blocks, but did not find a correlation between Openness to Feelings and sequence learning scores, which were taken as the difference between RT to a sequential block and to a control block in which the training sequence was removed. Similarly, Norman, Price, Duff, and Mentzoni (2007) administered a probabilistic SRT task but still found no significant correlation between Openness to Feelings and learning scores. It should be noted that the current study also did not find a zero-order correlation between the NEO Openness to Feelings facet and SRT learning. Indeed, SRT learning was more related to Openness to Aesthetics, Openness to Fantasy, and a preference for imagination, patterns, possibility, and beauty, as measured by the MBTI Intuition and BFAS Openness scales. Therefore, it might be argued that the core component of Openness that is related to individual differences in implicit learning is not openness to affective information, but an openness to the experience of aesthetics, patterns, and possibilities. Consistent with this idea, Pretz and Totz (2007) have argued that the MBTI Intuition scale has less to do with affective intuition, and is uniquely related to the holistic nature of intuition.

The current study also found a significant correlation between implicit learning and lack of deliberation. These results suggest that those who deliberate less may be more open to implicit learning since their selective attention will focus on a wider variety of stimuli, and thus be more likely to capture relevant associations. This idea is consistent with the reflective-impulsive model of Strack and Deutsch (2004), in which the reflective system is tied to explicit cognition whereas the impulsive system is related to the implicit system. Of course, it is also possible that good implicit learners naturally deliberate less because they have more confidence in the implicit learning domain. Future research should attempt to investigate the relation between impulsivity and implicit processing more thoroughly in order to determine the causal direction of the association.

5.3. Broader implications and limitations

The findings of the current study have implications for Reber's (1993) evolutionary theory of implicit learning, which predicts that because implicit learning ability is 'evolutionarily old', implicit processes should display tighter distributions and fewer individual differences in the general population than more 'evolutionarily recent' conscious processes. Although it may be the case that there is lower variability amongst humans in implicit learning than explicit learning, the current study suggests that individual differences in implicit learning are nonetheless meaningfully related to complex cognition and to personality. These individual differences deserve further study.

The results of the current study additionally have implications for skill acquisition research. Most theories of skill acquisition posit that the initial stages of learning draw strongly on explicit processes and general intelligence, which only later become automated and implicit (Ackerman, 1988; Anderson, 1993; Guttman, 1954; Marshalek, Lohman, & Snow, 1983). Our results suggest that the learning of a skill does not necessarily depend on deliberate processing in the initial stages. During interviews, none of the participants in the current study were able to articulate the underlying covariances in the implicit learning task, and a tendency for lack of deliberation was correlated with implicit learning, suggesting that they were building their tacit knowledge without deliberately trying to do so.

A limitation of the current study is that the split-half reliability of our implicit learning task was not high, even with our improved scoring method, suggesting that the assessment of individual differences in implicit learning was noisier than would be optimal. However, the level of reliability was standard for measures of implicit learning (Reber et al., 1991; Dienes, 1992). One might be concerned that the null results for correlation of implicit learning with psychometric intelligence and other explicit cognitive variables might simply reflect low reliability. However, other variables did show positive correlations with implicit learning, as hypothesized, and these effects were in the middle third of effect sizes reported in psychology ($r = .2$ to .3; Hemphill, 2003). We therefore conclude support for the hypothesis that implicit learning is either unrelated or only weakly related to individual differences in explicit cognition. Nonetheless, future studies should investigate ways to increase the reliability of assessment for implicit learning.

Another limitation of the current investigation was that it involved only one implicit learning task. We focused on the probabilistic version of the SRT because we believe it to be the best available measure of implicit learning (see Section 3). Since the sequential trials are continuously intermixed with a proportion of non-sequential trials, this probabilistic nature of the task makes it especially well suited to capture implicit learning effects (Jiménez & Vázquez, 2005; Schvaneveldt & Gómez, 1998), leading to less explicit knowledge. Interviews conducted after the experiment supported this notion—participants could not explicitly reproduce the sequential pattern. Nonetheless, conclusions about the associations between implicit learning and other constructs would gain strength if future research included both subjective (e.g., interviews) and objective (e.g., recognition or generation task performance) indices of explicit knowledge of the task.

Further, associations between implicit learning and other constructs would gain additional plausibility if they could be replicated using multiple implicit learning tasks and a latent implicit learning variable. Currently, our results cannot necessarily be generalized to other implicit learning paradigms. In order to strengthen the status of implicit learning as an independent ability, it will be necessary to show that other measures of implicit learning are not strongly related to *g*, and independently predict other important outcomes (Carroll, 1993). Although prior research has shown that various implicit learning paradigms do not correlate well with each other (Gebauer & Mackintosh, 2007, in preparation; Pretz et al., 2010; Salthouse et al., 1999), recent work by Gebauer and Mackintosh (in preparation) suggests that if enough implicit learning tasks are administered, a distinguishable factor, at least at the second order, does emerge.

Complicating the picture is the fact that implicit learning paradigms differ in the ratio of explicit to implicit processes required for successful performance on the tasks (Seger, 1994). Future research should administer a variety of implicit learning tasks which vary the extent to which explicit encoding during the learning phase is required. Researchers may have to construct new implicit learning tasks that minimize the effects of explicit learning in order for an implicit latent factor to emerge consistently. Additionally, Seger (1994) proposed the existence of both motor- and judgment-based forms of implicit learning. Some of the results of the current study may pertain only to motor-based implicit learning. The extent to which the current study's findings are generalizable to other forms of implicit learning remains an open question, as does the full range of implicit learning paradigms that evince meaningful individual differences.

A final issue is the extent to which performance on the SRT may reflect individual differences in something other than implicit learning. The SRT involves the learning of complex covariances not immediately transparent to the learner, and not relevant to the explicit goals of the task. Although we can be confident that individuals who respond faster to high- than to low-probable events have implicitly learned something about relative probabilities, we cannot rule out the possibility that those who show little or no difference in speed have learned something similar, but without this knowledge subsequently influencing their behavior. Therefore, the extent to which performance on the SRT is associated with individual differences in the ability to learn the covariances, individual differences in attentional focus (Jiménez, 2003; Shanks, 2003), or individual differences in cognitive style or personality (Kassin & Reber, 1979; Sternberg, 1997; Wolke & DuCette, 1974; Woolhouse & Bayne, 2000) remains uncertain. In other words, it is not yet clear at what stage of the implicit learning process individual differences are most salient—is it before the relevant stimuli receive selective attention or after, or is it even after associations have been learned but before they are expressed in behavior?

The answer to this question would have implications for Reber's (1993) evolutionary theory of implicit learning. It may indeed be the case that there is low variability amongst humans concerning the ability to acquire the rule structure of the environment, but that where humans vary is in other aspects of the process, such as the way in which they distribute the focus of their attention. Even with these limitations, we nonetheless see the investigation of individual differences in implicit cognition as a long neglected, but potentially fruitful, line of research.

6. Conclusion

Implicit learning can be assessed as an ability with individual differences that are meaningfully related to other important variables in individual differences research. Implicit learning ability was related to Openness to Experience and the associated construct, intuition, and to the tendency to make decisions without premeditation. Implicit learning ability was not related to psychometric intelligence, working memory, explicit associative learning, or self-rated Intellect. The pattern of variables that are and are not related to implicit learning is suggestive of conclusions about the structure of human information processing, consistent with the idea that there are two relatively independent systems by which individuals analyze and learn about regularities in their experience. Further, these results suggest that the investigation of individual differences in implicit cognition can increase our understanding of human intelligence, personality, skill acquisition, and language acquisition specifically, as well as human complex cognition more generally.

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