1. Introduction

We learn even when we are not aware of learning taking place. Implicit learning is the process of gaining sensitivity to novel relationships or regularities among events in the environment, which are often probabilistic in nature, without conscious knowledge of what has been learned or that learning has even occurred (Reber, 1989). Implicit learning is the process of gaining sensitivity to novel relationships among events in the environment, which are often probabilistic. It permits individuals to adapt their behavior to environments without expending conscious effort (Frensch and Rünger, 2003) and may be experienced as intuitions or “gut feelings” about the available choices (Lo and Repin, 2002). In other words, even though we may not be consciously aware of learning, our bodies may be subtly influencing our responses to patterns in environmental stimuli.

According to the somatic marker hypothesis (SMH; Bechara and Damasio, 2005; Damasio, 1996), autonomic activity plays a key role in implicit learning processes. The SMH suggests that physiological “markers” occur within individuals in response to encounters with stimuli and that with repeated exposure, these markers then become associated with those events. Somatic markers will be reactivated in response to those stimuli in future experiences, even without conscious awareness of the stimuli’s significance, and will bias cognitive processing and behavior involving them (for a review, see Dunn et al., 2006). Existing research supports the claim that somatic signals, at least initially, assist with learning in uncertain environments, but the majority of this research has focused only on activity in the sympathetic branch of the autonomic nervous system, and has largely ignored the parasympathetic branch.

The relationship between the brain and the autonomic nervous system is crucial to understanding the connection between the latter and individuals’ behavior. Both cortical and subcortical areas of the brain contribute to processes such as attentional regulation, affective information processing, and behavioral flexibility (Thayer and Lane, 2000). The coordinated activation of all of these processes is what allows individuals to adapt their behavior in the face of environmental challenges or changes (Thayer et al., 2012). For example, implicit learning involves a functional network of cortical–subcortical connections, with the prefrontal cortex acting as a hub that links brain regions related to memory and learning, such as the caudate nucleus (Yang and Li, 2012). In order to adapt behavior properly, there needs to be an appropriate balance between the sympathetic and parasympathetic nervous system (SNS and PNS, respectively); the former stimulates the body during stressful situations when a “fight-or-flight” response is needed and the latter promotes readiness to engage with (e.g., learn from) the environment. Research has suggested that this ability to regulate autonomic activity may be related to psychological self-regulation, which also relies on the prefrontal cortex to exert top-down control over other brain regions (Porges, 1992).

Given this, PNS activity may be particularly important to consider when examining individual differences in higher-order cognitive functioning. The current study focused on PNS activity and its role as a potential somatic marker in implicit learning. Although this is the first study on this topic, there is evidence that the PNS plays an important role in social and more explicit learning processes (Porges, 2007). To measure PNS activity, the impact of the vagus nerve, one of the primary conduits for parasympathetic influence on multiple organ systems, can be non-invasively assessed. Output from the brain, the nature of which is...
dependent on an individual's internal and external circumstances, travels to the heart via the vagus nerve. The vagus nerve acts like a "brake" on the heart (Porges, 2007), increasing cardiac output to facilitate blood flow for active problem solving or promoting fight-or-flight response (i.e., SNS activation) when the brake is withdrawn. The ability to flexibly engage and withdraw parasympathetic influence depending on internal and external demands is indicative of adaptive attentional and regulatory processes (Porges, 2003). This interplay of sympathetic and parasympathetic influence on the heart leads to variability in heart rate (i.e., heart rate variability or HRV). Because vagal activity fluctuates in phase with respiration (Frazier et al., 2004), researchers can document the variability in inter-beat intervals (i.e., the time between heartbeat beats) that occurs during typical breathing cycles, also known as high-frequency HRV (Bernston et al., 1997). This high-frequency HRV is also known as respiratory sinus arrhythmia (RSA). Therefore, RSA acts as an indirect measure of vagal-parasympathetic influence on the heart.

There is extensive research linking both RSA at rest as well as changes in RSA in response to a stressor (i.e., RSA reactivity) to a host of cognitive outcomes including explicit learning (Fairclough et al., 2005; Haley et al., 2008), executive functioning (Duschek et al., 2009; Hansen et al., 2003), fluid intelligence (Hinnant et al., 2013; Staton et al., 2009), and cognitive control (Marcovitch et al., 2010; Overbeek et al., 2014). Generally, this body of research suggests that a higher level of parasympathetic activity at rest (i.e., higher resting RSA) in conjunction with a decrease in parasympathetic activity in response to a challenge (i.e., RSA withdrawal) is associated with better cognitive performance. For instance, Hinnant et al. (2013) demonstrated that children with lower resting RSA and less RSA withdrawal during tasks measuring fluid cognition showed a significantly shallower slope of fluid cognitive performance across middle childhood. Fairclough et al. (2005) found that greater RSA withdrawal was associated with better performance on a demanding learning task and also predicted changes in performance across the task in a sample of young adults.

Notably, all of these cognitive tasks with which RSA have been associated are explicit in nature. Given that executive functions (i.e., attention, working memory) are an integral part of implicit learning and that prefrontal brain regions are active during this type of learning (Pascual-Leone et al., 1996; Simon et al., 2012; Yang and Li, 2012), it stands to reason that RSA may be related to implicit learning in a similar fashion. No research to date has examined the relationship between autonomic activity and performance on a task that specifically measures implicit learning. This study aims to fill that void by providing a more nuanced understanding of the physiological processes underlying implicit learning, and the possible implications for decision making under uncertainty. We investigated whether RSA measured at rest and during an implicit learning paradigm, the Triplets Learning Task (TLT; Howard et al., 2008), were associated with performance on that task.

Additionally, we examined the potential interaction between resting RSA and change in RSA during the task (RSA withdrawal) as a predictor of implicit learning. We hypothesized that individuals with higher resting RSA coupled with greater RSA withdrawal during implicit learning would demonstrate the most implicit learning, operationalized as better reaction time-based scores on the TLT.

2. Method

2.1. Participants

Seventy-one undergraduate students (37 females, 34 males) from a mid-Atlantic private university participated in this study. Participants were recruited through introductory psychology classes and received course credit as compensation. Data from two male participants were discarded because their ages (53 and 60 years old) did not warrant classification as a young adult, resulting in a final sample of 69 participants. This final sample had a mean age of 19.62 years (SD = 2.20), and its racial and ethnic composition closely matched that of the university, with 55 participants identifying themselves as White (79.7%), three as Black (4.3%), two as Asian (2.9%), eight as Hispanic or Latino (11.6%), and one as Native Hawaiian or Pacific Islander (1.4%). The university’s Institutional Review Board approved all procedures, and the participants provided informed consent prior to administration of any measures.

2.2. Procedure

The researcher seated the participant in front of the testing computer and manually adhered nine electrodes to the participant’s skin in order to collect data on autonomic activity. The sensors were connected to a Mindware physiological data collection system, and data on the participants’ RSA were obtained. The researcher instructed the participant to sit quietly during a five-minute acclimation period and a subsequent three-minute resting baseline assessment. Then the participant completed a measure of implicit learning, the Triplets Learning Task (TLT; Howard et al., 2008), followed immediately by a two-minute TLT recognition test, described in detail by Howard et al. (2008), to determine if learning was truly implicit. Upon completion, participants were debriefed and received compensation for their time.

2.3. Measures

2.3.1. Triplets Learning Task (TLT)

Participants completed the TLT (Howard et al., 2008), a task used to assess implicit probabilistic associative learning in both younger and older adults (e.g., Simon et al., 2012). Individuals viewed a single row of four empty circles on the computer screen and observed events (i.e., a circle filling in red or green) occurring on each trial. Each trial was comprised of a three-event sequence, or a “triplet,” consisting of two consecutive red “cues” and a green “target” event, as depicted in Fig. 1.

Participants were instructed to observe the first two cue events without responding and to press a key corresponding to the location of the target event. Four buttons on the computer keyboard were used for responding with the middle and index finger of each hand (“z”, “x”, “y”, and “v” corresponding to the four circle locations in left-to-right order, respectively). Fig. 1 provides a detailed depiction of the timing on each trial of the TLT. Reaction time (RT) was recorded (in milliseconds) from the presentation of the target event to the participant’s initial response. The target remained on the screen for a fixed amount of time before disappearing. Then an empty row of circles was displayed for 650 ms until the next trial began. Unbeknownst to participants, the location of the first cue predicted one of the four target locations on 80% of the trials (high-probability triplet) and was followed by one of the other three target locations on 20% of the trials (low-probability triplet). The second cue was always randomly selected, thereby creating a second-order probabilistic relationship between the first cue event and the target event. All 64 possible triplets were presented across the trials of the task, with the six unique combinations of cue-target mappings counterbalanced across the sample. Participants were instructed to respond as quickly and accurately as possible to the location of the green circle (target) on each trial.

Participants performed two successive sessions, each containing ten blocks of 50 trials for a total of 1000 trials per person, and so they were encouraged to rest between blocks for no > 30 s to avoid fatigue. Following Simon et al. (2010), end-of-block feedback was provided to guide participants toward an overall accuracy level of 92%. The triplet type effect (TTE)—the average difference in RT to low-probability and high-probability triplets—was calculated for each participant and was used as the indicator of implicit learning in subsequent analyses (Stillman et al., 2014). Immediately after completion of the TLT, explicit awareness was probed using a sensitive recognition test (Howard et al., 2008), during which participants observed 64 triplets in a random
order and rated each as having occurred frequently (“1”) or infrequently (“2”) during the experiment.

2.3.2. Respiratory sinus arrhythmia (RSA)

Electrocardiogram (ECG) signals were recorded from two electrodes, one placed approximately two centimeters (cm) under the participant’s right clavicle and the other between the two bottom ribs on the participant’s left side, and then analyzed using a commercial software package (MindWare Technologies Ltd., Columbus, OH). Respiration was recorded through four Ag/AgCl ECG electrodes, two of which were placed about three cm apart on the participant’s chest, and two of which were positioned about three cm apart vertically on the mid and lower spine, and was calculated through spectral analysis of thoracic impedance (Zo; Ernst et al., 1999). High-frequency HRV, or RSA, was calculated as the changes in the R-R (interbeat) interval occurring between 0.15 and 0.40 Hz. Minute-by-minute estimates of RSA during baseline and the computerized task were computed through spectral analysis of these heart beat series using a fast Fourier transformation, and correction of errors in the automated marking of R-waves was performed manually by trained coders. The physiological variables used as predictors in subsequent analyses were calculated as the average RSA value during the three-minute baseline period (i.e., resting RSA) and the difference between the average RSA during the TLT and resting RSA (i.e., RSA reactivity). More specifically, a positive reactivity value indicates RSA augmentation during learning while a negative value indicates greater RSA withdrawal during learning.

3. Results

3.1. Preliminary analyses

3.1.1. TLT

To facilitate examination of change over time, the TLT was broken down into four, five-block epochs. Nine RT and accuracy outlier data points (i.e., ≥ 3.5 SD from the mean) were removed, and two types of low-probability triplets—repetitions (e.g., 1–1–1, 2–2–2, etc.) and trills (e.g., 1–2–1, 2–1–2, etc.)—were removed due to the fact that individuals often show preexisting response tendencies (Howard et al., 2004). Median RTs were determined by triplet type (high- vs. low-probability) for each participant on each block. The data were then averaged across adjacent blocks to produce a single mean RT for each triplet type and participant on each of the four epochs. A similar procedure was also used before analyzing the accuracy data.

RT data from the TLT was analyzed using a 4 (epoch) × 2 (triplet type) repeated measures analysis of variance (ANOVA), and the data are plotted in Fig. 2. Statistical significance was set at α = 0.05, and two-tailed tests were used. A Greenhouse-Geisser correction was applied to the degrees of freedom when Mauchly’s test indicated a violation of the assumption of sphericity. This analysis revealed a significant main effect of epoch, $F(1.56, 104.63) = 58.56, p < 0.001$, indicating general skill learning or overall faster responding with practice, as well as a significant main effect of triplet type (TT), $F(1, 67) = 28.15$, $p < 0.001$, demonstrating overall sequence-specific learning (i.e., faster responding to high- vs. low-probability triplets). The significant epoch × TT interaction illustrated an increased difference in RT to high- and low-probability triplets over the course of the task, $F(2.26, 151.20) = 9.57, p < 0.001$. A repeated measures ANOVA on the accuracy data produced a significant main effect of TT, $F(1, 64) = 6.02, p = 0.017$, as well as a marginally significant main effect of epoch, $F(2.61, 167.02) = 2.37, p = 0.081$, and interaction, $F(2.74, 175.03) = 2.62, p = 0.052$. There was no evidence of a speed-accuracy trade-off. These findings imply that individuals were more accurate in responding to the high- than low-frequency triplets, and there was a trend for this difference to increase across the task. Overall, these data suggest that individuals demonstrated sequence-specific learning on the TLT.
3.1.2. TLT recognition
For the recognition task, reps and trills were included in the analysis and we examined only responses made to the initial presentation of a particular triplet. A repeated measures ANOVA produced a marginally significant main effect of TT on frequency ratings, F(3, 207) = 2.27, p = 0.082. Post-hoc paired-samples t-tests revealed a significant difference between high-probability triplets and repetitions (p = 0.037) as well as high-probability triplets and trills (p = 0.020), as expected (Howard et al., 2004). Importantly, the difference between high- and low-probability triplets was not significant, indicating that the learning that occurred during the TLT was implicit in nature.

3.2. Primary analysis

3.2.1. Descriptive statistics
Table 1 presents the means and standard deviations for the study variables. As expected, there was a significant negative relationship between resting RSA and RSA reactivity (i.e., RSA during the TLT minus resting RSA), r(63) = −0.41, p = 0.001, suggesting that higher RSA at rest was associated with greater RSA withdrawal during the TLT. TTE scores from the second and third epoch of the TLT were positively related, r(66) = 0.42, p < 0.001, while the association between TTE scores from the second and fourth epochs almost reached significance, r(66) = 0.23, p = 0.065. There was also a positive relationship between TTE scores on the third and fourth epoch, and r(66) = 0.39, p = 0.001.

3.2.2. RSA predicts TLT
We conducted a repeated measures ANOVA to examine whether resting RSA, RSA reactivity and their interaction predicted change over time in learning on the TLT. Learning was operationalized as the triplet type effect (TTE)—the average difference between RT to low- and high-probability triplets—and was calculated for each participant on each of the four epochs. A positive TTE value indicates, on average, faster responding to high- relative to low-probability triplets. Results showed a significant main effect of RSA reactivity, F(3, 177) = 3.74, p = 0.012, as well as a resting RSA × RSA reactivity interaction, F(3, 177) = 3.99, p = 0.009. Fig. 3 displays the patterns of learning over time for individuals at ± 1 SD from the average values of resting RSA and RSA reactivity. Individuals with higher resting RSA and greater RSA withdrawal demonstrated the greatest learning by the end of the task. Additionally, the change in TTE across the task for these individuals was steeper than for individuals with other combinations of resting RSA and RSA reactivity.

4. Discussion
This study was the first to investigate whether parasympathetic activity at rest and during an implicit learning task predicted change over time in implicit learning. An understanding of the associations between autonomic activity and implicit learning may have implications for explaining why some individuals are risk-seeking and others are risk-averse under conditions of uncertainty. According to the SMH (Damasio, 1996), learning is the mechanism through which somatic processes have their impact on decision making. Learning that informs decision making likely begins implicitly as the brain subconsciously detects patterns in stimuli and then becomes more explicit as these detected patterns are used to inform higher-level cognitive processes. Through afferent (information to the brain) and efferent (information from the brain) neuronal pathways, in many cases the body reacts to these patterns of stimuli before we are consciously aware of them, creating intuitions or “gut feelings” about situations and behaviors.

Implicit learning has been shown to play a role in performance on the Iowa Gambling Task (IGT; Bechara et al., 1994), in which participants repeatedly draw from any of four card decks and receive monetary rewards and punishments on each selection that vary in magnitude and frequency. At the outset of the IGT, participants are unaware that two of the decks will ultimately yield a net gain (i.e., advantageous decks), while the other two will yield a net loss (i.e., disadvantageous decks). With what begins as trial-and-error, individuals explore their options and carry forward with them information pertaining to the outcomes they experience. Over the course of the task, learning is illustrated through individuals selecting significantly more often from the advantageous relative to the disadvantageous decks (Bechara et al., 1994).

Previous research with the IGT has shown that individuals exhibit autonomic arousal in anticipation of engaging a decision (Crone et al., 2004; Crone and van der Molen, 2007; Drucaroff et al., 2011). Bechara et al. (1997) examined the skin conductance responses (SCRs) of patients with prefrontal damage—a cause of impaired decision making—and healthy controls, and found that only the controls displayed increases in draws from advantageous decks on the IGT. Moreover, only the controls exhibited SCRs before choosing a disadvantageous deck, suggesting that repeated experiences with the choice-outcome contingencies of the various decks enabled healthy participants to form markers in response to them. These markers appeared to guide behavior implicitly, at least initially, as evidenced by the participants’ inability to describe their reasons for preferring certain decks. In support of Bechara et al. (1997), Crone et al. (2004) found that only participants who performed well overall on the IGT (i.e., those who learned) displayed a slowed heart rate and increased SCRs before selecting the disadvantageous decks. While this research provides support for a connection between autonomic nervous system activity and learning, this work has primarily focused on SNS activity.

We focused on the role of the PNS in implicit learning due to associations between the former and more explicit cognitive processes including executive functioning, working memory, and fluid intelligence (Duschek et al., 2009; Fairchild et al., 2005; Haley et al., 2008; Hansen et al., 2003; Hinnant et al., 2013; Marcovitch et al., 2010; Overbeek et al., 2014; Staton et al., 2009), as well as the fact that the prefrontal cortex.
plays a prominent role in PNS activity and in the functional networks active during learning and memory (Thayer et al., 2012; Thayer and Lane, 2000; Yang and Li, 2012). PNS activity was operationalized through RSA, an indirect measure of vagus nerve influence on the heart. High levels of resting RSA and RSA withdrawal are thought to indicate a general physiological readiness and capability to engage with environmental agents (Porges, 2003), largely due to self-regulatory processes initiated by the prefrontal cortex (Thayer et al., 2012; Thayer and Lane, 2000). Given that the prefrontal cortex also plays a large role in implicit learning (Pascual-Leone et al., 1996; Simon et al., 2012; Yang and Li, 2012), we hypothesized that higher resting RSA and greater RSA withdrawal may promote implicit learning during exposure to subtle, and in this case probabilistic, regularities. We found that young adults with this combination of parasympathetic arousal and reactivity exhibited the steepest slope of learning across the task. While individuals with this pattern of resting RSA and RSA reactivity in the current study demonstrated approximately equivalent implicit learning to others early on, as they continued to subconsciously observe the regularities in the task, they exhibited stronger performance. By the third epoch of task, these individuals evidenced greater learning than those with other combinations of resting RSA and RSA reactivity. Importantly, the recognition task confirmed that learning on the task was implicit as evidenced by the failure of participants to differentiate patterns of high- and low-probability triplets. Overall, this suggests that RSA is not only an index of physiological readiness for the environment, but psychological as well. This is the first study to illustrate that any index of autonomic activity is specifically associated with performance on an implicit learning task. Repeated decisions made under uncertainty (i.e., with probabilistic outcomes) necessarily involve implicit learning as individuals begin to discern patterns in the data and to make use of those patterns to inform future decisions. The Iowa Gambling Task is a prime example of such a condition in research, though implicit learning, explicit learning, and decision making are difficult to differentiate in this measure. Mata et al. (2011) explain that learning choice-outcome contingencies over time is a crucial part of decision making under uncertainty. This learning may occur implicitly so that people can acquire information about the environment and make advantageous decisions without exerting conscious effort (Frensch and Rünger, 2003). Our findings suggest that PNS activity, as measured by RSA, may play an important role as a somatic marker in implicit learning, and that patterns of higher resting PNS levels and greater PNS reactivity may facilitate implicit learning processes. These same processes may play a key role in decision making under conditions of uncertainty by making some individuals more sensitive to or better able to detect patterns in stimuli, and therefore better able to adapt or regulate their behavior. While this study addresses a major gap in the existing literature by examining the relations between autonomic activity and implicit learning, it does have some limitations. One limitation is our inability to document autonomic reactivity to high- and low-probability triplets separately. The temporal resolution of autonomic measures is incommensurate with the fluid, event-based design of the implicit learning task, the TLT. Thus, innovative future work might investigate the feasibility of discerning the effects of autonomic indices on learning under different conditions of stimuli frequency (i.e., do autonomic activity effects differ depending on the familiarity of the event). Future research should also consider developmental aspects of implicit learning and how links between autonomic processes and implicit learning change over time in order to better understand how decision-making processes develop. Previous research has demonstrated age differences in implicit learning across adulthood (Mata et al., 2011). However, little is currently known about changes in implicit learning across childhood and adolescence, except for conclusions inferred from work using tasks that are not entirely implicit, such as the IGT (e.g., Crone et al., 2004). While resting RSA appears to be moderately stable in childhood, RSA reactivity shows less stability (El-Sheikh, 2005). Longitudinal work investigating RSA stability during adolescence to early adulthood and its association with implicit learning could help to clarify whether RSA plays a role in the dramatic increases in risky decision making and risk-taking behaviors that occur during this often emotionally stressful period.

**References**


