“You Can’t Hide Your Lyin’ Eyes”: Investigating the Relationship Between Associative Learning, Cue Awareness, and Decision Performance in Detecting Lies

Ben W. Morrison, Australian College of Applied Psychology, Australia, and Charles Sturt University, Australia, **David Johnston**, Australian College of Applied Psychology, Australia, and Cambridge University, UK, **Mathew Naylor**, Australian College of Applied Psychology, Australia, and The University of Sydney, Australia, **Natalie M. V. Morrison**, Western Sydney University, Australia, and **Daniel Forrest**, The University of Sydney, Australia

Although skilled cue utilization is presumed to result primarily from domain-specific experience, individual differences in learning are theorized to play a significant role. Using a single-group correlational design, this study tested whether individuals’ domain-general associative learning capacity was related to performance in a complex real-world decision task presumed to rely heavily on cues: lie detection. A total of 21 participants completed an associative learning task in the form of a Space Invaders-like game. In the game, those who learn the cues are able to respond faster to the appearance of an enemy ship. Participants were also surveyed on their awareness of cues in the game. This was followed by a lie detection task. It was hypothesized that greater associative learning would be associated with greater awareness of cues in the learning task, and subsequently, superior accuracy in the lie detection task. Participants’ associative learning was correlated with their cue awareness (r_{pb} = .782, p < .001). Further, learning was associated with better performance in the lie detection task (r = .544, p = .011); however, accuracy was found to be unrelated to the types of cues reportedly used during detection. These findings have implications for our understanding of cue acquisition and expertise development.

Address correspondence to Ben W. Morrison, School of Psychology, Charles Sturt University, Building 1400, Panorama Avenue, Bathurst, NSW 2795, Australia, bmorrison@csu.edu.au.

Journal of Cognitive Engineering and Decision Making
Vol. 14, No. 2, Month XXXX, pp. 1-13
DOI:10.1177/1555343420918084
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Keywords: cue utilization, cue acquisition, expertise, lie detection, learning

Cues are events, whether internal (e.g., a mood) or external (e.g., a sound), that upon their recognition will signal significance to an individual. In this sense, cues “trigger” associations held in memory, which, when valid, enable us to make predictions (or diagnoses) about our environment (Wiggins, 2015). When engaged appropriately, cues enable relatively rapid and effective decision making (Klein, 2008; Mann et al., 2007). Cognitively demanding contexts (e.g., medicine, aviation, criminal investigation, clinical psychology, professional sport) appear to encourage individuals to engage cues regularly, given their ability to reduce cognitive load during decision making (Crane et al., 2018; Johnston & Morrison, 2016; Morrison et al., 2013; Morrison & Morrison, 2015; (Wiggins et al., 2014). Indeed, Easterbrook (1959) established that in such environments, which are typically characterized by an increased arousal state, decision makers’ attention becomes more selective, targeting the most relevant cues for processing, while filtering out the superfluous ones

Greater cue utilization has been shown to be critical in the generation of efficient and accurate responses across a range of work domains (Brouwers et al., 2017; Gacasan & Wiggins, 2017; Morrison et al., 2018; Perry et al., 2013; Wiggins et al., 2018) and is a commonly cited strategy among experts (Johnston & Morrison, 2016; Kahneman & Klein, 2009; Loveday et al., 2013). A process of cue refinement called cue discrimination has also been associated with expertise (Shanteau & Hall, 1992). Experts appear to rely on fewer cues than their novice counterparts, only selecting and using the most relevant ones (Shanteau, 1992). In a study that compared expert and novice critical care cardiovascular nurses, it was shown that only a limited number of cues were used by expert nurses across a range of decision scenarios (Reischman & Yarandi, 2002). These "critical" cues tend to be associated with fewer hypotheses, which assist in more timely and accurate assessments (i.e., they are relatively high in what has been termed "diagnosticity"; Schriver et al., 2008).

Many have highlighted the role of cue recognition in skilled intuition (Hertwig et al., 1999; Kahneman & Klein, 2009; Simon, 1992). In considering an expert's ability to rapidly size up a situation, Simon (1992) posits that "The situation has provided a cue: This cue has given the expert access to information stored in memory, and the information provides the answer. Intuition is nothing more and nothing less than recognition" (p. 155). The model of intuition as cue recognition has instigated a simple yet powerful explanatory framework in the naturalistic decision making (NDM) community.

The recognition-primed decision (RPD) model (Klein, 1993; Klein et al., 1986) extends on Simon's premise, offering an account of how experienced decision makers will leverage cues in the initial stages of situation assessment. The model posits that experienced decision makers will use cues to draw on a repertoire of stored patterns, which accumulate as a result of domain-specific experiences. In matching these patterns, the expert will nonconsciously generate and prioritize a series of plausible responses, which they can test via a process of mental simulation (a notion consistent with deGroot's concept of "progressive deepening"; 1978). Thus, for NDM researchers, cues are thought to initiate the intuitive aspect of the RPD model, which incorporates both intuitive and analytical phases. Indeed, in a dual-system model of cognition (Evans et al., 2009; Stanovich & West, 2000), cue utilization will occur as part of the associative machinery of System 1 (the rapid, automatic, unconscious, and relatively effortless processor), while simulation and deepening are better aligned to System 2 (slow, controlled, deliberate, and relatively effortful).

CUE ACQUISITION AND LEARNING

Cue utilization has been hypothesized to result from previous environmental experience (Wiggins, 2006). Decision makers are presumed to require an opportunity to observe potential cues and receive feedback upon their application (Kahneman & Klein, 2009). Here, it may be reasoned that deliberate engagement of System 2 during learning will work to sensitize our System 1 to the detection of relevant cues in the environment, harnessing the associative power of System 1. However, while experience with the operational environment is a necessary condition for the development of skilled intuition, it is not a sufficient one.

In addition to factors that influence our ability to acquire cues, such as the relative validity of the operational environment (Kahneman & Klein, 2009), it is apparent that some decision makers will learn more than others from equivalent experiences (Ericsson et al., 2006; Klein, 2015), and this will invariably influence their rate of cue acquisition. Indeed, a recent study questioned whether the capacity to learn cues may be partly trait-driven. Wiggins and Auton (2016) examined cue utilization among transmission power controllers and found that those who displayed greater cue utilization in the context of power control also displayed greater levels of cue utilization in a non-domain-specificcontext. This suggested that cue behaviors may be partly determined by inherent characteristics of the decision maker. Despite the consistent findings with regard to cue utilization and performance advantages, only limited research has explored the underlying mechanisms that would lead to individual differences in cue acquisition and utilization. This would appear to be theoretically relevant to the process of learning.

It can be reasoned that the initial identification and resultant utilization of cues must involve some learning process through which the association and meaning are established. Numerous theorists have developed explanatory frameworks for the acquisition of associations in human memory (e.g., Anderson & Bower, 1973; Mandler, 2002). However, ultimately, the mechanism by which humans learn that two events are associated remains under contention.

A number of researchers have suggested that people learn through rule-based mechanisms involving the use of higher cognitive processes through a process of generation and evaluation about the associations (Lovibond & Shanks, 2002). This notion would imply significant involvement from System 2 mechanisms. Opposing this are researchers who maintain that learning can proceed as the result of capturing regularities within the environment, a stimulus-driven process whereby associations are automatically formed between these representations, favoring a System 1 view of development (Clark et al., 2002). Thus, one of the key differences between these theories of associative memory appears to be the degree of conscious awareness a learner has regarding stimulus contingencies.

While much of the NDM literature would support the notion that experts' tacit knowledge, including their use of cues, is typically unconscious and difficult to retrieve, cognitive interview techniques have proven successful in eliciting stimulus contingencies from experienced operators across numerous domains. For instance, in a recent study of cue utilization among Rugby League players, Johnston and Morrison (2016) used the Critical Decision Method (CDM; Crandall & Getchell-Reiter, 1993) to reveal that players' processes relating to cue utilization were consciously adaptive in response to a dynamic environment. As such, it was hypothesized that experts' awareness of cues allows for a continual reordering of cue significance. In contrast, novices are seemingly less aware of cues and hence, their utilization is less amenable to change.

Awareness has also been conceptualized as a powerful and sophisticated selection mechanism, which enables individuals to focus attention toward a restricted set of objects and events (Eriksen & Yeh, 1985; Treisman & Gelade, 1980). This is consistent with an information reduction hypothesis in the cognitive–perceptual skills literature (Haider & Frensch, 1999), which posits that much of the performance advantage associated with cue utilization stems from their attention management properties. Studies of awareness have thus concentrated on measures of attention.

The study of a phenomenon called "inattentional blindness," the failure to notice an object when attention is focused elsewhere (Mack & Rock, 1998), has revealed that regardless of whether the subjects noticed the unexpected object or not, all observers spent on average the same amount of time looking at the unexpected object (Koivisto et al., 2004). Further to this, in expert–novice domain-relevant paradigms of inattentional blindness, skilled performers were less susceptible to inattentional blindness in dynamic situations (Memmert, 2006). This suggests that awareness may also relate to cognitive efficiencies, a process modeled by Anderson's Adaptive Control of Thought—Rational (ACT-R) theory (1996). Despite the apparent usefulness of this model, no research has explored individual variations in learning and its subsequent effects on the development of these "chunks" and condition action statements.

Irrespective of the theoretical perspective one subscribes to regarding the mechanisms involved in the formation of associations, it is clear that their acquisition underpins learning. Thus, it is reasonable to posit that a domain-general associative learning capacity will likely play a fundamental role in the early stages of expertise development. This notion is comparable to how other cognitive abilities predict individual differences in complex task performance early in learning (Ward et al., 2019). However, it is typically less clear whether such abilities remain predictive after extensive task exposure.

Whilst it is presumed that such abilities are likely to be later mitigated or supplanted by domain-specific mechanisms, we posit that in many domains they will remain predictive nonetheless. Indeed, like other domain-general abilities (e.g., intelligence, attentional control, working memory capacity), associative learning capacity may partly explain why some individuals will advance to higher levels of expertise than others with similar experience levels. However, unlike other domain-general abilities, the relationship between learners' domain-general associative learning capacity and decision-making performance in real-world contexts is largely untested. Further, investigations of the role of individuals' awareness of the associations in their learning, which would presumably have implications for instructional design (e.g., explicit instruction vs. guided discovery), are similarly limited. The current paper seeks to address these gaps by testing whether domain-general associative learning is associated with performance differences in a complex real-world task. The study also examined the degree of relation between learners' rate of domain-general associative learning and their awareness of acquired associations.

Lie Detection as a Context for Studying Cue Utilization

Lie detection represents a sound context for addressing our research questions as (1) it represents a complex real-world task in which objective performance is readily measured; (2) performance is presumed to rely heavily on the use of a broad range of cues (e.g., facial features, tone and pitch of voice, word/sentence length and complexity, speech rate, interaction behaviors with interviewers and co-conspirators); (3) it is a task that most people will have had extensive exposure to in their everyday lives (without formal training); and (4) some individuals are able to develop a degree of expertise in the domain, despite the lack of well-defined knowledge and rules.

Interest in lie detection has been a focus of study for almost half a century (Vrij, 2008). Researchers have systematically investigated the behaviors that probabilistically signal deception (DePaulo et al., 2003), and it is presumed that such behaviors are able to manifest in cue-based associations. Indeed, Ekman and Friesen (1969) theorized two broad categories of cues that emanate from the deceiver: leakage and deception cues. Leakage cues refer to nonverbal cues that reveal what the liar is trying to hide. Deception cues indicate that deception may be occurring without indicating the nature of the information that is being concealed.

Different approaches to nonverbal deceptive behavior have been theorized around the different control approaches used by the deceiver: the cognitive, emotional, and the attempted control approach (Vrij, 2008). The cognitive approach assumes that lying is more cognitively complex than telling the truth, hence liars will make more mistakes (Vrij, 2008). The emotional approach suggests that a liar can feel either guilt, fear, or excitement and that each emotional state will lead to an observable bodily motion such as microexpressions (Ekman et al., 1991). The attempted control approach proposes that a liar in their attempt to control specific aspects of their presentation will paradoxically display a cue to reveal deception that has occurred (Greene et al., 1985). Supporting these theories, in the most comprehensive analysis of cues to deception, DePaulo et al. (2003) showed that there existed a number of cues that may be helpful in distinguishing between lie and truth. Since then, other researchers have uncovered a range of additional cues (Driskell et al., 2012; Fuller et al., 2013; Vrij & Granhag, 2014).

Study Aims and Hypotheses

The aim of the current study was to test whether domain-general associative learning capacity was related to performance in a complex real-world decision task presumed to rely heavily on cues: lie detection. Further, we explored the relationship between decision makers' awareness of associations during learning and their domain-general associative learning capacity. Participants were required to complete an associative learning task in the form of a Space Invaders-like video game (consistent with the method of Forrest et al., 2016). In the game participants had to respond quickly to a target stimulus (an "enemy spaceship") that appeared intermittently among distractor stimuli ("friendly spaceships"). Although participants were given no indication that they could learn to predict the appearance of the enemy ship, specific distractor stimuli acted as a potential cue to its impending appearance. Thus, those who successfully learned the cue would be faster to respond to the appearance of the enemy ship. This task also included an explicit awareness measure developed by Forrest et al. (2016) to gauge the participants' degree of awareness of the associations (i.e., the cues).

Participants then viewed 12 videos of people who were placed in a high-stakes mock crime paradigm (ascertained from ten Brinke et al., 2014). After each video, participants were required to answer a forced-choice question relating to whether or not the person in the video was lying or telling the truth.

If conscious awareness is a prerequisite to association acquisition, we would expect to see a positive relationship between participants' domain-general associative learning capacity and their awareness of stimulus contingencies in the associative learning task. We would also expect that those participants who demonstrate a greater capacity for domain-general associative learning will have developed a superior repertoire of domain-specific lie detection patterns over time, which will result in a concomitant advantage in detecting lies. Therefore, it was hypothesized that those participants demonstrating a greater degree of domain-general associative learning would show (1) greater awareness of the cues in the learning task and (2) greater accuracy in the lie detection task. Additionally, the cues identified by participants were categorized based on cue typology commonly cited in the extant literature (Sporer, 1997; Sporer & Schwandt, 2006): nonverbal visual (e.g., eye contact, head movements); paraverbal (e.g., response latencies, pauses); verbal content (e.g., use of certain words, consistency of a statement); combined verbal type (i.e., verbal and paraverbal); and combined (i.e., nonverbal visual, paraverbal, and verbal content). The categorization process enabled an investigation of the potential association between cue type and lie detection accuracy.

METHOD

Participants

Participants comprised a sample of convenience and were recruited through an online social media platform and a research recruitment portal (i.e., SONA) at the Australian College of Applied Psychology. There were 21 participants (18 female) aged between 23 and 47 (M = 30.57, SD = 6.93). All participants required normal color vision and hearing for eligibility. The research was approved by the institution's Human Research Ethics Committee.

Apparatus and Materials

The associative learning task acquired from Forrest et al. (2016) was programmed with Python on Windows 7 and was run on Macintosh Computers operating through Windows, connected to 22″ LCD monitors of 1920 × 1080 resolution, refreshed at a rate of 60 Hz. Responses were recorded using a standard computer keyboard.

Associative Learning Task. Learning task stimuli comprised nine differently colored and differently shaped images 200 × 200 pixels in size, each representing unique ships. The colors used were blue, cyan, green, light green, orange, pink, purple, red, and yellow. A 400 × 800 pixel image of a green and blue semicircle represented planet Earth at the bottom of the screen, and the outer border of the game area was a red semicircle. Distance from the red border to the edge of the planet measured 28 cm. All images appeared on a black background and the game-related text was white. See Figure 1 for a screen shot of the associative learning task.

Of the nine stimuli, eight were designated as "friendly" while one was an enemy ship. Six of the eight friendly ships were distractors. Purple was selected as the enemy ship after a previous experiment revealed it mostly effectively avoided the salience of brighter colors, had no preexisting stereotypes of meaning, and was differentiated from other colors more equally (Forrest et al., 2016). The other ships, both the cues (two) and distractors (i.e., no signal to enemy ship; six), were required to differ sufficiently in shape and color both to the enemy ship and to each other, and colors were again selected in line with Forrest et al.'s (2016) advice.

Accuracy in the learning task was measured as a percentage of the enemy ships that participants correctly eliminated before reaching the planet. The degree of associative learning was calculated by taking the difference between participants' response times (RTs in milliseconds; ms)

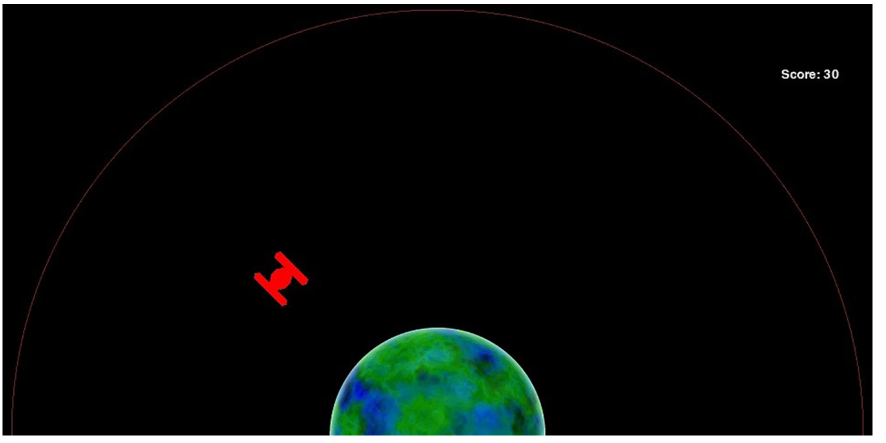

Figure 1. Example of the associative learning task game display.

in shooting the enemy ship in response to the cue ships, compared to shooting it in the absence of a prompt. In this sense, a greater difference in RT equated to greater evidence of domain-general associative learning.

Awareness Measure. Participants completed an explicit "awareness" measure (Forrest et al., 2016) to ascertain their understanding of the relationship between the cue ships and the enemy ship that they signaled. The questionnaire used a free recall component in which participants were asked whether they could predict the appearance of the enemy ship. Awareness was ascertained as to whether the participant could verbally identify the relationship between the enemy ship and the friendly ships that preceded it).

Lie Detection Task. Participants viewed 12 prerecorded interviews from a close midshot, whereby each character was visible from the middle chest upwards and the face clearly seen. The videos were ascertained from ten Brinke et al. (2014) who placed psychology students in a high-stakes mock crime paradigm (consistent with Kircher, Horowitz, & Raskin, 1988). In their study, participants (N = 12; 6 male, 6 female) were randomly assigned to steal or not steal $100 (steal condition, n = 6; no-steal condition, n = 6). Participants were told that they would earn the $100 if they convinced the experimenter that they had not stolen the money or lose $100 if they failed to convince the experimenter (regardless of whether they had). Participants were told that they would be entered into a lottery to win an additional $500 if they were successful. During the recorded interview they were asked a range of questions including baseline questions (e.g., "What are you wearing today?") and interview questions (e.g., "Did you steal the money?"). Each video lasted an average of 97 s (SD = 21.62 s).

Following the viewing of each video, participants provided a direct, self-report decision as to whether each character was lying (i.e., "In your opinion was the respondent lying?"). Next, participants were asked about the features of the video that informed their decision. Participants were provided an example to help elicit the potential cues that were used in the process of their decision making: "Consider you believe a person looked tired, the cues you may have used could be frequent yawning and red eyes." A lie detection accuracy score was computed for participants by summing the number of correct instances of lie detection across the 12 presentations.

Procedure

The participants completed the study in individual sessions. Participants were positioned to be oriented toward the screen and instructed that they would be required to maintain the same position while playing the game. Participants were then instructed to place noise cancellation headphones over their ears, which would remain on for the remainder of the study. Participants were then instructed to play the computer game with the aim of scoring the highest amount of points possible.

The game involved colored spacecraft entering from two points around a semicircular boundary, 90° apart, and approaching a planet at the center in a direct trajectory. Text-based instructions then appeared on-screen informing participants to allow friendly ships to land and to prevent enemy ships from landing by pressing either the left or right shift keys to shoot ships from the left or right entry points, respectively. Doing so caused a red beam to emerge from the planet and destroy the ship on the corresponding side. For friendly ships, safe entrance to the planet was indicated by a short bubble animation, an accompanying positive sound, and a "10" pop-up. If destroyed, friendly ships showed a short neutral animation, a neutral sound, and a "−10" pop-up. When enemy ships were destroyed, an explosion animation and sound were played followed by a "50" pop-up whereas if not destroyed, a negative sound would play, the planet would turn red, and a "−50" pop-up was displayed. Participants were not told which ships were friendly or hostile. Instead, they were told that they would learn as they played.

The game consisted of three blocks, each lasting 306 seconds (s), allowing for two breaks. Stimuli included eight friendly ships and one enemy ship. Two of the friendly ships acted as potential cues, which reliably signaled the incoming enemy ship. Enemy ships reliably followed the cue ships, and occasionally followed a distractor stimulus. At the completion of one block, on-screen text informed participants to have a short break if required. Two further 306-s blocks followed, divided by a break, until the end of the third block where participants were informed that the study had ended and to wait for the researcher. Each trial lasted 1 s and only one stimulus was displayed on-screen at any given time. Each stimulus took 0.5-s to reach the planet. Thus, one trial consisted of 0.5-s stimulus exposure followed by a 0.5-s gap before the next trial began.

Following completion of this task, participants completed the awareness measure. They were required to fill out a form enquiring about what methods they used to predict the arrival of the oncoming enemy ship. Once completed the form was returned to the researcher.

The researcher then opened up an online questionnaire, which was displayed in Qualtrics (Qualtrics LLC, Provo, UT, USA). Participants were directed to follow instructions that appeared on-screen. Participants first completed a demographics questionnaire. Once completed participants were presented with an instruction informing them that "You are about to view a video of a person either lying or telling the truth. Pay close attention because you will be asked a series of questions about this." When ready, participants pressed the next button to continue and subsequently viewed the deception stimuli. Videos could only be viewed on a singular occasion. Following the viewing of the video, participants were then required to answer a series of questions relating to the potential presence of deception in the video and the features of the videos that they used to base their decision on. Once all questions were completed, participants would select the "next button" and be primed by an instruction screen. This screen informed the participant that they were about to view another video. The participant would select "next" before being able to view the next deception stimuli. Videos of lying and truth telling were randomly interspersed for the participants and followed the same trial structure of priming, stimuli, and questions about stimuli for a total of 12 trials. Following the completion of the 12 trials, participants were presented with an on-screen instruction informing them that they had completed the study. Participants were then debriefed by the researcher.

RESULTS

Lie Detection

Overall accuracy scores were computed through summing the lie detection accuracy in each of the 12 presentations, and ranged from 16.67% to 66.67% (M = 38.89, SD = 16.94, N = 21).

Associative Learning, Awareness, and Lie Detection Accuracy

Mean reaction times (RTs) were recorded in ms, and the degree of associative learning was calculated by taking the difference between participants' RT in shooting the enemy ship in response to the cue ships, compared to shooting it in the absence of a prompt. In this sense, a greater difference in RT equated to greater evidence of domain-general associative learning.

Individuals were coded based on their "awareness." Awareness was ascertained as to whether the participant could verbally identify the relationship between the enemy ship and the friendly ships that preceded it. After meeting the associated mathematical assumptions, data were subjected to correlational analyses to investigate the potential relationship between domain-general associative learning capacity, awareness of cues in the learning task, and subsequent accuracy in the lie detection task. A point-biserial correlational analysis revealed a statistically significant positive correlation between associative learning and awareness, r_{pb} $(N = 21) = .782$, $p < .001$ (large effect). Similarly, Pearson's correlational analysis revealed a statistically significant positive correlation between associative learning and lie detection performance, r $(N = 21) = .544$, $p = .011$ (large effect). These results indicate that a greater degree of associative learning in the initial learning task was associated with greater awareness of cues present in the learning task and greater performance on the lie detection task.

Deception Cues

A directed content analysis was conducted to categorize the cues that were used by each participant in the analysis. Cue categorization was based on cue typology commonly cited in the extant literature (Sporer, 1997; Sporer & Schwandt, 2006): nonverbal visual (e.g., eye contact, head movements), paraverbal (e.g., response latencies, pauses), and verbal content cues (e.g., use of certain words, consistency of a statement), combined verbal type (i.e., verbal and paraverbal), and combined (i.e., nonverbal visual, paraverbal, and verbal content cues).

The categorization process enabled an investigation of the potential association between cue type and lie detection accuracy; however, a two-way χ^2 revealed a nonsignificant association, χ^2 $(4, N = 21) = 2.373$, $p = .667$. The frequencies are shown in Table 1.

DISCUSSION

The aim of the current study was to test whether domain-general associative learning capacity was related to performance in a complex real-world decision task presumed to rely heavily on cues: lie detection. Further, we explored the relationship between decision makers' awareness of associations and their associative learning capacity. As hypothesized, the results revealed a significant positive relationship between participants' domain-general associative learning capacity and their awareness of cues in the learning task. Further, learning was found to be positively associated with

TABLE 1: Frequencies, Percentages, and Adjusted Standardized Residuals (ASR) for Correct and Incorrect Lie Detection When Using the Five Different Cue Types

	Correct Lie Detection				Incorrect Lie Detection				
Cue Type	f	%	f_e	ASR[a]	f	%	f_e	ASR[a]	Total
Nonverbal visual	22	45.8	20.5	0.5	26	54.2	27.5	−0.5	48
Paraverbal	8	32	10.7	−1.2	17	68	14.3	1.2	25
Verbal content	13	38.2	14.6	−0.6	21	61.8	19.4	0.6	34
Combined	51	44	49.6	0.4	65	56	66.4	−0.4	116
Verbal combined	7	53.8	5.6	0.8	6	46.2	7.4	−0.8	13

lie detection performance. Additionally, the cues identified by participants were categorized based on cue typology commonly cited in the extant literature (Sporer, 1997; Sporer & Schwandt, 2006); however, no association was found between cue type and lie detection accuracy.

Lie Detection

The current findings regarding lie detection accuracy rates (38.89%) were of dissimilar magnitude to those reported in a previous meta-analysis (54%; Bond & DePaulo, 2006). This difference could be a reflection in the variability of stimuli used across studies. Indeed, the current findings were more similar to ten Brinke et al. (2014) who, using the method adopted in the current study, found a mean detection accuracy rate of 43.75%.

Associative Learning

As anticipated, "aware" participants demonstrated a superior associative learning rate compared to those who were found to be "unaware." Forrest et al. (2016) explained that this was due to participants having conscious awareness of contingencies, which was priming faster reaction times to cued trials. Unexpectedly, compared to Forrest et al. (2016), proportionately fewer participants reported an explicit awareness of the cue ships that signaled the enemy ship, only 14% compared to 25% in Forrest et al. (2016). This may be due to adaptations in the task, which involved participants' active involvement (pressing space in response to stimuli) as opposed to Forrest et al.'s (2016) design, which involved a noninstructed observation. This could have promoted the use of more complex strategies rather than a search for simple associations.

Deception Cues

The analysis revealed that there was no one category of cue that was better able to identify deception. This would support a previous meta-analysis that revealed that there exists no one consistent and reliable indicator to detecting deception (Bond & DePaulo, 2006). Within the context of this study, participants reported that they tended to use multiple (i.e., combined) cues in trying to detect deception; however, this strategy was also not found to be more accurate than any singular cue. These findings may also allude to participants' difficulties in consciously recognizing and/or articulating the cues they use. This is consistent with the findings of ten Brinke et al. (2014) who found that indirect, nonconscious measures of deception detection were significantly more accurate than direct, explicit measures.

Our findings regarding the types of cues used may also have been stifled by the artificial nature of the task and the static nature of the available cues. Indeed, recent trends in lie detection findings emphasize the importance of the active interaction between the observer and the deceiver in the inducement of deception cues (e.g., Hartwig et al., 2014). Future studies examining cue utilization in this context should consider the design of methods that enable a more dynamic interaction between observer and deceiver. Further, greater attention should be paid to cultural differences that may greatly influence cue meaning (e.g., pitch of voice has been shown to signal deception in some cultures, and conversely, truth-telling in others; Matsumoto et al., 2015).

Associative Learning, Awareness, and Lie Detection Accuracy

In line with the researchers' hypothesis, there existed a significant relationship between participants' domain-general associative learning capacity and lie detection accuracy. Previous research has highlighted that individual differences with regard to learning exist; however, the implications of these differences have not been explored. The finding that an individual's domain-general associative learning capacity correlated with performance might partly explain why the ability to detect deceit has been found to generalize across different scenarios (Frank & Ekman, 1997).

The current findings are consistent with the ACT-R framework (Anderson, 1996). The ACT-R theory provides an understanding of how knowledge structures are formed and activated in the performance of a skill. ACT-R proposes that learning is accomplished in two stages. First, the user must learn the facts and store the facts as chunks in memory. The first stage has two components, a learning process and a storage phase. Second, these chunks of facts must be converted into decision rules. This study investigated one component of this first stage (learning) and showed that this process had cumulative effects on the whole system. It is hypothesized that awareness is related more significantly to the second stage where what is learned is reformulated into decision rules. It is suggested that the interplay between a learning system and awareness of associations may represent qualities leading to enhanced cognitive development. This could have implications for training, as it would suggest that interventions could be tailored for either those who require exposure-based training (i.e., “unaware”) or those who require more explicit instructions (i.e., “aware”). However, we underline here that while our findings are superficially consistent with an ACT-R framework, the methods we have employed do not provide a direct test of cognitive architecture. As such, our conclusions are constrained to the identification of a domain-general associative learning mechanism that may play a role in to-be-acquired domain-specific mechanisms. More work is required to gain understanding in how the domain-general mechanisms identified here contribute to valid cue utilization behaviors, which will primarily arise out of extensive domain-specific experiences. The outcomes of such work would undoubtedly have significant theoretical and applied implications. For instance, understanding the extent to which simple, domain-general measures remain predictive of complex task performance in specific domains has the potential to inform training and selection procedures.

Limitations

The approach taken in this research contributes to theoretical models of expertise development but carries with it limitations. One significant issue stems from the fact that the same outcome can be produced by indiscernible variations between higher level cognitive structures and lower level processes. This is related to the context-dependency issue, reflected in the problem of one–many relations (Zalta, 2005). It is known that there is a one–many relation between neural pathways and higher level cognitions, such that a learning mechanism can causally lead to or be part of different higher level states depending on the context in which it is activated (Smith & Vela, 2001).

It must be noted that while “aware” participants in our study appeared to have an advantage in this domain, the factors that mediate the space between domain-general learning abilities and domain-specific decision performance have not been explored here. Indeed, while it is argued here that formation of associations represent the most fundamental building block of skilled intuition, it is presumed that much of the advantage to decision performance will arise from a range of cognitive skills not examined here (e.g., problem detection, sensemaking, and uncertainty management). Thus, it is with caution that the current findings should be interpreted.

The approach to studying the nature of cue utilization adopted in the study was also somewhat limited. A range of methodologies have been developed for investigating cue-related behavior, such as eye-tracking techniques, response latency-based recognition tasks (Morrison et al., 2013), and cue assessment batteries (e.g., EXPERTise; Loveday et al., 2014). These methods would provide a richer and more precise set of data in relation to users’ cue search behavior, recognition, and discrimination and should be considered in extending the current line of investigation. Further, those wishing to continue using the lie detection paradigm as a context for studying expertise development may consider other known factors that may influence cue utilization in the domain (e.g., the use of global heuristics and truth biases; Feeley & deTurck, 1995).

Finally, while the sample size employed in the study is considered adequate for a single-group design (Field, 2013), it may somewhat limit the strength of the conclusions drawn here. The behavioral nature of the methodology employed and the time commitment required from participants presents challenges for future researchers wishing to extend on the current design.

Future Directions

Whilst this research has shown a correlation between learning differences and performance in a complex real-world task, it demands a deeper investigation into these underlying processes. As an example, individual differences in perception of time have been observed (Gilaie-Dotan et al., 2010), but no study has focused on the broader implications. Of specific interest to deception, microexpressions occur at a time threshold of 230 ms, which falls outside levels of conscious awareness (Yan et al., 2013). This would suggest that time perception would invariably play a role in having the capacity to observe and a learning process efficient enough to analyze this. However, the debate within psychology surrounding unconscious processes influencing the conscious is controversial. Whilst neuroscience appears to support the notions of an automatic associative system (Bargh & Morsella, 2008), the learning field continues to advocate for the causal role of awareness in learning (Weidemann et al., 2016).

The role of feedback in cue acquisition also requires closer investigation. The learning of "real-world" cues will require a degree of feedback to reinforce the fledgling association, which may be less available or timely than the feedback seen in the associative learning task used here (Kahneman & Klein, 2009). How decision makers learn cues in contexts with nonexplicit or no feedback is largely unclear. This is potentially problematic for work domains where formulated decisions are met with delayed, minimal, or even no feedback regarding their efficacy. For instance, a health practitioner may receive only sporadic and delayed feedback about a diagnosis or choice of intervention. In such cases, the decision maker is presumably limited in their capacity to learn about potential predictive cues that might help develop their expertise.

One current hypothesis is that learning can be driven by decision makers' confidence when performance feedback is of poor quality or absent. Hainguerlot et al. (2018) demonstrated that successful learning of the predictive value of cues in the absence of external feedback was positively related to decision makers' confidence judgments, which was understood to be a superior meta-cognitive ability to distinguish between correct responses and errors. The role of such metacognitive abilities in the acquisition of cue-based associations warrants further investigation, particularly in domains characterized by a limited opportunity for explicit feedback.

Conclusion

The current findings suggest that participants' inherent capacity for domain-general associative learning can be related to their decision performance in complex real-world decision tasks, in this case, lie detection. Further, this learning capacity was found to be positively related to participants' conscious awareness of learned associations. While the factors that mediate the space between the domain-general learning abilities and domain-specific decision performance have not been explored here, the findings offer insight into the initial processes involved in cue acquisition and expertise development.

ORCID iD

Ben W. Morrison https://orcid.org/0000-0002-5026-4675

REFERENCES

Anderson, J. R. (1996). Act: A simple theory of complex cognition. *American Psychologist*, *51*(4), 355–365. https://doi.org/10.1037/0003-066X.51.4.355

Anderson, J. R., & Bower, G. (1973). *Human associative memory*. distributed by the Halsted Press division of John Wiley & Sons, Washington, D.C.

Bargh, J. A., & Morsella, E. (2008). The unconscious mind. *Perspectives on Psychological Science*, *3*(1), 73–79. https://doi.org/10.1111/j.1745-6916.2008.00064.x

Bond, C. F., & DePaulo, B. M. (2006). Accuracy of deception judgments. *Personality and Social Psychology Review*, *10*(3), 214–234. https://doi.org/10.1207/s15327957pspr1003_2

Brouwers, S., Wiggins, M. W., Griffin, B., Helton, W. S., & O'Hare, D. (2017). The role of cue utilisation in reducing the workload in a train control task. *Ergonomics*, *60*(11), 1500–1515. https://doi.org/10.1080/00140139.2017.1330494

Clark, R. E., Manns, J. R., & Squire, L. R. (2002). Classical conditioning, awareness, and brain systems. *Trends in Cognitive Sciences*, *6*(12), 524–531. https://doi.org/10.1016/S1364-6613(02)02041-7

Crandall, B., & Getchell-Reiter, K. (1993). Critical decision method: A technique for eliciting concrete assessment indicators from the "intuition" of NICU nurses. *Advances in Nursing Sciences*, *16*(1), 42–51.

Crane, M. F., Brouwers, S., Wiggins, M. W., Loveday, T., Forrest, K., Tan, S. G. M., & Cyna, A. M. (2018). "Experience isn't everything": How emotion affects the relationship between experience and cue utilization. *Human Factors: The Journal of* *the Human Factors and Ergonomics Society*, *60*(5), 685–698. https://doi.org/10.1177/0018720818765800

deGroot, A. D. (1978). *Thought and choice in chess*. Mouton.

DePaulo, B. M., Lindsay, J. J., Malone, B. E., Muhlenbruck, L., Charlton, K., & Cooper, H. (2003). Cues to deception. *Psychological Bulletin*, *129*(1), 74–118.

Driskell, J. E., Salas, E., & Driskell, T. (2012). Social indicators of deception. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *54*(4), 577–588. https://doi.org/10.1177/0018720812446338

Easterbrook, J. A. (1959). The effect of emotion on cue utilization and the organization of behavior. *Psychological Review*, *66*(3), 183–201. https://doi.org/10.1037/h0047707

Ekman, P., & Friesen, W. V. (1969). Nonverbal leakage and clues to deception. *Psychiatry*, *32*(1), 88–106. https://doi.org/10.1080/00332747.1969.11023575

Ekman, P., O'Sullivan, M., Friesen, W. V., & Scherer, K. R. (1991). Invited article: Face, voice, and body in detecting deceit. *Journal of Nonverbal Behavior*, *15*(2), 125–135. https://doi.org/10.1007/BF00998267

Ericsson, K. A., Charness, N., Hoffman, R. R., & Feltovich, P. J. (Eds.). (2006). *The Cambridge handbook of expertise and expert performance*. Cambridge University Press.

Eriksen, C. W., & Yeh, Y. Y. (1985). Allocation of attention in the visual field. *Journal of Experimental Psychology: Human Perception and Performance*, *11*(5), 583. https://doi.org/10.1037//0096-1523.11.5.583

Evans, J., St B. T., & Frankish, K. (Eds.). (2009). *In two minds: Dual processes and beyond*. Oxford University Press.

Feeley, T. H., & deTurck, M. A. (1995). Global cue usage in behavioral lie detection. *Communication Quarterly*, *43*(4), 420–430. https://doi.org/10.1080/01463379509369989

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics* (4th Ed). SAGE Publications Inc.

Forrest, D. R. L., Mather, M., & Harris, J. A. (2016). Unmasking latent inhibition in humans. *The Quarterly Journal of Experimental Psychology*, 1–18.

Frank, M. G., & Ekman, P. (1997). The ability to detect deceit generalizes across different types of high-stake lies. *Journal of Personality and Social Psychology*, *72*(6), 1429–1439. https://doi.org/10.1037/0022-3514.72.6.1429

Fuller, C. M., Biros, D. P., Burgoon, J., & Nunamaker, J. (2013). An examination and validation of linguistic constructs for studying high-stakes deception. *Group Decision and Negotiation*, *22*(1), 117–134. https://doi.org/10.1007/s10726-012-9300-z

Gacasan, E. M. P., & Wiggins, M. W. (2017). Sensemaking through cue utilisation in disaster recovery project management. *International Journal of Project Management*, *35*(5), 818–826. https://doi.org/10.1016/j.ijproman.2016.09.009

Gilaie-Dotan, S., Kanai, R., & Rees, G. (2010). Individual differences in time perception indicate different modality-independent mechanisms for different temporal durations. *Journal of Vision*, *10*(7), 1407–1407. https://doi.org/10.1167/10.7.1407

Greene, J. O., O'Hair, H., Cody, M. J., & Yen, C. (1985). Planning and control of behavior during deception. *Human Communication Research*, *11*(3), 335–364. https://doi.org/10.1111/j.1468-2958.1985.tb00051.x

Haider, H., & Frensch, P. A. (1999). Information reduction during skill acquisition: The influence of task instruction. *Journal of Experimental Psychology: Applied*, *5*(2), 129–151.

Hainguerlot, M., Vergnaud, J.-C., & de Gardelle, V. (2018). Metacognitive ability predicts learning cue-stimulus associations in the absence of external feedback. *Scientific Reports*, *8*(1), 5602. https://doi.org/10.1038/s41598-018-23936-9

Hartwig, M., Granhag, P. A., & Luke, T. (2014). Strategic use of evidence during investigative interviews: The state of the science. In D. C. Raskin, C. R. Honts, & J. C., Kircher (Eds.), *Credibility assessment: Scientific research and applications* (pp. 1–36). Academic Press.

Hertwig, R., Hoffrage, U., & Martingnon, L. (1999). Quick estimation: Letting the environment do the work. In G. Gigerenzer, P. M. Todd, & A. B. C. Research Group (Eds.), *Simple heuristics that make us smart* (pp. 37–58). Oxford University Press.

Johnston, D., & Morrison, B. W. (2016). The application of naturalistic decision-making techniques to explore cue use in rugby League Playmakers. *Journal of Cognitive Engineering and Decision Making*, *10*(4), 391–410. https://doi.org/10.1177/1555343416662181

Kahneman, D., & Klein, G. (2009). Conditions for intuitive expertise: A failure to disagree. *American Psychologist*, *64*(6), 515, 526–526. https://doi.org/10.1037/a0016755

Kircher, J. C., Horowitz, S. W., & Raskin, D. C. (1988). Meta-analysis of mock crime studies of the control question polygraph technique. *Law and Human Behavior*, *12*(1), 79–90.

Klein, G. (2008). Naturalistic decision making. *Human Factors*, *50*(3), 456–460. https://doi.org/10.1518/001872008X288385

Klein, G. A. (1993). A recognition-primed decision (RPD) model of rapid decision making. In G. A. Klein, J. Orasanu, R. Calderwood, & C. E. Zsambok (Eds.), *Decision making in action: Models and methods* (pp. 138–147). Ablex.

Klein, G. (2015). A naturalistic decision making perspective on studying intuitive decision making. *Journal of Applied Research in Memory and Cognition*, *4*(3), 164–168.

Klein, G. A., Calderwood, R., & Clinton-Cirocco, A. (1986). Rapid decision making on the fireground. In *Proceedings of the Human Factors and Ergonomics Society 30th Annual Meeting* (Vol. 1, pp. 576–580). Ablex.

Koivisto, M., Hyönä, J., & Revonsuo, A. (2004). The effects of eye movements, spatial attention, and stimulus features on inattentional blindness. *Vision Research*, *44*(27), 3211–3221. https://doi.org/10.1016/j.visres.2004.07.026

Loveday, T., Wiggins, M. W., Harris, J. M., O'Hare, D., & Smith, N. (2013). An objective approach to identifying diagnostic expertise among power system controllers. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *55*(1), 90–107. https://doi.org/10.1177/0018720812450911

Loveday, T., Wiggins, M. W., & Searle, B. J. (2014). Cue utilization and broad indicators of workplace expertise. *Journal of Cognitive Engineering and Decision Making*, *8*(1), 98–113. https://doi.org/10.1177/1555343413497019

Lovibond, P. F., & Shanks, D. R. (2002). The role of awareness in Pavlovian conditioning: Empirical evidence and theoretical implications. *Journal of Experimental Psychology: Animal Behavior Processes*, *28*(1), 3–26.

Mack, A., & Rock, I. (1998). *Inattentional blindness* (Vol. 33). MIT press.

Mandler, G. (2002). Origins of the cognitive (r)evolution. *Journal of the History of the Behavioral Sciences*, *38*(4), 339–353. https://doi.org/10.1002/jhbs.10066

Mann, D. T. Y., Williams, A. M., Ward, P., & Janelle, C. M. (2007). Perceptual-cognitive expertise in sport: A meta-analysis. *Journal of Sport and Exercise Psychology*, *29*(4), 457–478. https://doi.org/10.1123/jsep.29.4.457

Matsumoto, D., Hwang, H. C., & Sandoval, V. A. (2015). Ethnic similarities and differences in linguistic indicators of veracity and lying in a moderately high stakes scenario. *Journal of Police and Criminal Psychology*, *30*(1), 15–26. https://doi.org/10.1007/s11896-013-9137-7

Memmert, D. (2006). The effects of eye movements, age, and expertise on inattentional blindness. *Consciousness and Cognition*, *15*(3), 620–627. https://doi.org/10.1016/j.concog.2006.01.001

Morrison, B. W., & Morrison, N. M. V. (2015). Diagnostic cues in major crime scene investigation. In M. W. Wiggins & T. Loveday (Eds.), *Diagnostic expertise in organisational environments* (pp. 91–98). Ashgate.

Morrison, B. W., Morrison, N. M. V., Morton, J., & Harris, J. (2013). Using critical-cue inventories to advance virtual patient technologies in psychological assessment. In H. Shen, R. Smith, J. Paay, P. Calder, & T. Wyeld (Eds.), *Proceedings of the 25th Australian Computer-Human Interaction Conference: Augmentation, Application, Innovation, Collaboration (OzCHI '13)* (pp. 531–534). ACM.

Morrison, B. W., Wiggins, M. W., Bond, N. W., & Tyler, M. D. (2013). Measuring relative cue strength as a means of validating an inventory of expert offender profiling cues. *Journal of Cognitive Engineering and Decision Making*, *7*(2), 211–226. https://doi.org/10.1177/1555343412459192

Morrison, B. W., Wiggins, M. W., & Morrison, N. M. V. (2018). Utility of expert cue exposure as a mechanism to improve decision-making performance among novice criminal investigators. *Journal of Cognitive Engineering and Decision Making*, *12*(2), 99–111. https://doi.org/10.1177/1555343417746570

Perry, N. C., Wiggins, M. W., Childs, M., & Fogarty, G. (2013). The application of reduced-processing decision support systems to facilitate the acquisition of decision-making skills. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *55*(3), 535–544. https://doi.org/10.1177/0018720812467367

Reischman, R. R., & Yarandi, H. N. (2002). Critical care cardiovascular nurse expert and novice diagnostic cue utilization. *Journal of Advanced Nursing*, *39*(1), 24–34. https://doi.org/10.1046/j.1365-2648.2000.02239.x

Schriver, A. T., Morrow, D. G., Wickens, C. D., & Talleur, D. A. (2008). Expertise differences in attentional strategies related to pilot decision making. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *50*(6), 864–878. https://doi.org/10.1518/001872008X374974

Shanteau, J. (1992). Competence in experts: The role of task characteristics. *Organizational Behavior and Human Decision Processes*, *53*(2), 252–266. https://doi.org/10.1016/0749-5978(92)90064-E

Shanteau, J., & Hall, B. (1992). How much information does an expert use? Is it relevant? *Acta Psychologica*, *81*(1), 75–86. https://doi.org/10.1016/0001-6918(92)90012-3

Simon, H. A. (1992). What is an "Explanation" of behavior? *Psychological Science*, *3*(3), 150–161. https://doi.org/10.1111/j.1467-9280.1992.tb00017.x

Smith, S. M., & Vela, E. (2001). Environmental context-dependent memory: A review and meta-analysis. *Psychonomic Bulletin & Review*, *8*(2), 203–220. https://doi.org/10.3758/BF03196157

Sporer, S. L. (1997). The less travelled road to truth: Verbal cues in deception detection in accounts of fabricated and self-experienced events. *Applied Cognitive Psychology*, *11*(5), 373–397.

Sporer, S. L., & Schwandt, B. (2006). Paraverbal indicators of deception: A meta-analytic synthesis. *Applied Cognitive Psychology*, *20*(4), 421–446.

Stanovich, K. E., & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate? *Behavioral and Brain Sciences*, *23*(5), 645–665. https://doi.org/10.1017/S0140525X00003435

ten Brinke, L., Stimson, D., & Carney, D. R. (2014). Some evidence for unconscious lie detection. *Psychological Science*, *25*(5), 1098–1105. https://doi.org/10.1177/0956797614524421

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*(1), 97–136. https://doi.org/10.1016/0010-0285(80)90005-5

Vrij, A. (2008). *Detecting lies and deceit: Pitfalls and opportunities*. Wiley.

Vrij, A., & Granhag, P. A. (2014). Eliciting information and detecting lies in intelligence interviewing: An overview of recent research. *Applied Cognitive Psychology*, *28*(6), 936–944. https://doi.org/10.1002/acp.3071

Ward, P., Maarten Schraagen, J., Gore, J., Roth, E., Hambrick, D., Burgoyne, A., & Oswald, F. (2019). Domain-General Models of Expertise: The Role of Cognitive Ability. In *The Oxford Handbook of expertise*. Oxford University Press.

Weidemann, G., Satkunarajah, M., & Lovibond, P. F. (2016). I think, therefore eyeblink: The importance of contingency awareness in conditioning. *Psychological Science*, *27*(4), 467–475.

Wiggins, M. W., Azar, D., Hawken, J., Loveday, T., & Newman, D. (2014). Cue-utilisation typologies and pilots' pre-flight and in-flight weather decision-making. *Safety Science*, *65*, 118–124.

Wiggins, M. W. (2006). Cue-based processing and human performance. In W. Karwowski (Ed.), *International encyclopedia of Ergonomics and human factors* (2nd ed.pp. 641–645). Taylor & Francis.

Wiggins, M., & Auton, J. (2016). *Trait-based cue utilisation in diagnostic settings*. Paper presented at the 2016 APS Congress, Melbourne, Victoria, Australia.

Wiggins, M. W. (2015). Cues in diagnostic reasoning. In M. W. Wiggins & T. Loveday (Eds.), *Diagnostic Expertise in Organizational Environments* (pp. 1–11). Ashgate Publishing.

Wiggins, M. W., Whincup, E., & Auton, J. C. (2018). Cue utilisation reduces effort but increases arousal during a process control task. *Applied Ergonomics*, *69*, 120–127. https://doi.org/10.1016/j.apergo.2018.01.012

Yan, W. J., Wu, Q., Liang, J., Chen, Y.-H., & Fu, X. (2013). How fast are the leaked facial expressions: The duration of micro-expressions. *Journal of Nonverbal Behavior*, *37*(4), 217–230. https://doi.org/10.1007/s10919-013-0159-8

Zalta, E. (2005). *Stanford encyclopedia of philosophy*. Stanford University.

Ben W. Morrison is a senior lecturer and organizational psychologist working at Charles Sturt University, Australia. His research focuses on psychology in the workplace, including areas relating to human factors, cognitive engineering, cybersecurity, safety, human–computer interaction, automation, and expertise development.

David Johnston is a registered psychologist with research experience in clinical and sporting domains. He has experience working clinically in inpatient and community settings specializing in mood and anxiety disorders. David is an award winning researcher, winning the Australian Psychological Society Prize for his research investigating expert decision making in sport.

Mathew Naylor is a PhD candidate who has completed a Bachelor of Psychological Sciences (Honors) with a first class award. He is currently investigating how virtual reality can be combined with mindfulness and relaxation in order to help office workers to better cope with stress. Matt has an interest in cyberpsychology, video games, and gaming and internet cultures.

Natalie M. V. Morrison (PhD, MPsychClin) is a registered psychologist who works in both acute and community mental health settings. She presently works as an academic at the School of Medicine, Western Sydney University, teaching mental health to undergraduate and postgraduate medical students. Natalie's research interests started in cognitive psychology, specifically attentional modeling, but has since extended into areas related to trauma, chronic pain, and suicide prevention.

Daniel Forrest is a provisionally registered psychologist with experience in experimental and clinical research. His research areas include human and animal learning, memory, pain, and mindfulness-based interventions.