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1 **Topic choice: Cognition**

2 **The role of cue-based strategies in skilled diagnosis amongst pathologists**

3 Carrigan, A.J.^{1,2}, Charlton, A.,³ Foucar, E.⁴, Wiggins, M.W.^{1,2}, Georgiou, A.⁵,
4 Palmeri, T.⁶, & Curby, K.M.^{1,2}.

5
6 *¹Department of Psychology, Macquarie University, Sydney, Australia.*

7 *²Centre for Elite Performance, Expertise & Training, Macquarie University, Sydney,*
8 *Australia.*

9 *³Department of Histopathology, Auckland City Hospital, and Department of Molecular*
10 *Medicine and Pathology, University of Auckland, New Zealand.*

11 *⁴Department of Pathology, University of New Mexico, Albuquerque, USA.*

12 *⁵Centre for Health Systems and Safety Research, Macquarie University, Sydney, Australia.*

13 *⁶Department of Psychology, Vanderbilt University, Nashville, United States.*

14
15 **Author Contact Details:**

16 Dr Ann Carrigan,
17 Centre for Elite Performance, Expertise, and Training
18 Department of Psychology
19 Macquarie University,
20 North Ryde, NSW 2109
21 Australia.
22 Email: ann.carrigan@mq.edu.au
23

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34 **Running Head:** Cue based strategies in Pathology

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Precis

Expertise in pathology involves accurate, reliable, and timely responses. Using a sample of histopathologists, we established differences in cue utilization that, independent of cases read per year, explained differences in their capability to accurately recognize abnormalities in static images. This has implications for the development of pathological skills in practice.

43 **Objective:** This research was designed to test whether behavioral indicators of pathology-
44 related cue utilisation were associated with performance on a diagnostic task.

45 **Background:** Across many domains, including pathology, successful diagnosis depends on
46 pattern recognition that is supported by associations in memory in the form of cues. Previous
47 studies have focused on the specific information or knowledge on which medical image
48 expertise relies. The target in this study is the more general ability to identify and interpret
49 relevant information.

50 **Method:** Data were collected from fifty-four histopathologists in both conference and online
51 settings. The participants completed a pathology edition of the Expert Intensive Skills
52 Evaluation 2.0 (EXPERTise 2.0) to establish behavioral indicators of context-related cue
53 utilization. They also completed a separate diagnostic task designed to examine related
54 diagnostic skills.

55 **Results:** Behavioral indicators of higher or lower cue utilisation were based on the
56 participants' performance across five tasks. Accounting for the number of cases reported per
57 year, higher cue utilisation was associated with greater accuracy on the diagnostic task. A
58 post hoc analysis suggested that higher cue utilisation may be associated with a greater
59 capacity to recognise low prevalence cases.

60 **Conclusion:** This study provides support for the role of cue utilization in the development
61 and maintenance of skilled diagnosis amongst pathologists.

62 **Application:** Pathologist training needs to be structured to ensure that learners have the
63 opportunity to form cue-based strategies and associations in memory, especially for less
64 commonly seen diseases.

65

66 **Keywords:** Medical Image Perception, Cue Utilization, Cognitive Load, Prevalence.

67

68 Histopathology is a medical pathology sub-specialty, the role of which involves the
69 examination of tissue to correctly identify tissue features that are normal, normal variants and
70 clinically significant pathological processes. Correct interpretation can require integration of
71 morphological findings with clinical history. Pathologists visually inspect histopathological
72 slides using a light microscope allowing for the interpretation and classification of diseases.
73 Typically, tissue biopsy or resections referred to histopathologists from a variety of medical
74 specialists have already been subjected to diagnostic tests to confirm pathology, thereby
75 creating an environment where disease prevalence tends to be high. The diagnosis rendered
76 by the histopathologist, is considered the gold standard and often the starting point for
77 determining the patient's treatment and prognosis. This is especially critical for breast cancer,
78 where early diagnosis results in a 97%, 5-year or more survival rate (Australian Institute of
79 Health and Welfare (AIHW), 2009).

80 Errors within diagnostic medicine more broadly are estimated at > 10% (Goldman et
81 al., 1983; Hoff, 2013; Kirch & Schafii, 1996; Shojania et al., 2003). In pathology, errors in
82 cancer diagnosis are reported at up to 12% (Raab et al., 2005). The discrepancy between
83 breast cancer staging among breast histopathologists is at a high of 40% (Elmore, et al.,
84 2015). Elmore and colleagues (2015) conducted a large study in the US with 115 practicing
85 pathologists and showed a 24.7% disagreement rate among pathologists interpreting breast
86 biopsies. This rate was higher for denser breasts, among pathologists who interpreted lower
87 weekly case volumes, worked in smaller practices or non-academic settings.

88 Unfortunately, errors that occur in pathology and diagnostic medicine can of course
89 have grave consequences. For example, the under-interpretation of an atypical cancer may
90 delay the required treatments (false negatives or misses) and conversely an overdiagnosis of
91 normal tissue may lead to unnecessary invasive treatments (false positives or false alarms).
92 These issues are complicated as the base rate for histopathology is non-normal. In practice,

93 there are programs in place which record a pathologist's performance and provide the
94 necessary feedback. For example, the Royal College of Pathologists of Australasia (RCPA)
95 offers a Quality Assurance Program (QAP) in which pathologists must participate to maintain
96 their registration. Given that the pathology diagnosis is final and definitive, it is important to
97 explain the underlying processes involved in these crucial, diagnostic decisions and therefore,
98 how errors might be prevented.

99 Nodine and Krupinski (1998), and more recently, Drew et al. (2013), proposed that
100 successful diagnosis results when medical image specialists apply their fine-tuned perceptual
101 and cognitive skills to rapidly process a layout/scene globally to reach their decision.
102 Consistent with this account, abnormalities in a display or image can be detected rapidly,
103 following a brief glance (Brennan et al., 2018; Carmody et al., 1981; Carrigan et al., 2018;
104 Charness, 1996; Evans et al., 2013). Amongst cytologists, performance is above chance at
105 detecting abnormalities in micrographs of cervical smears presented for 250ms (Evans, et al.,
106 2013). Similarly, expert radiologists and pathologists fixate more rapidly than trainees on an
107 abnormality and do so using fewer visual saccades (Kundel & La Follette, 1972; Kundel &
108 Nodine, 1975; Kundel et al., 1978; Krupinski et al., 2013).

109 Krupinski, et al. (2013) characterised the scanning patterns of resident pathologists
110 (pathologists in training) throughout their training and demonstrated their search patterns
111 changed from a less efficient strategy (scanning around the entire visual field) to a more
112 efficient strategy (targeted search) with experience. Further, visual expertise is associated
113 with less time fixating on diagnostically irrelevant and non-diagnostic regions (Brunye et al.,
114 2014; Krupinski et al., 2013). These capabilities suggest that experts extract global properties
115 of an image rapidly and develop a finely tuned perceptual representation that almost instantly
116 supports the relationship between visual stimuli and a diagnosis. This ability is also likely

117 supported by patterns in memory gained through past experience that are triggered when
118 presented with the stimulus (Brunye et al., 2014).

119 According to Nodine & Mello-Thoms (2010), when an expert considers a case,
120 ‘features’ that are extracted during the initial glance are compared against a template or
121 ‘pattern’ in memory. This process tends to be rapid, non-conscious, and domain-specific and
122 is dependent upon a repertoire of feature-event/object associations in memory that serve as
123 ‘cues’ (Brunswick, 1955; Croskerry, 2009; Klein, 1989; Wiggins, 2014; 2020; Wiggins,
124 Brouwers, Davies, et al., 2014). Carrigan et al. (2019) demonstrated that compared with non-
125 radiologists, radiologists perceive features that are especially diagnostic to the case (subtle
126 nodule in a chest radiograph) as more salient, lending support to the notion that feature-based
127 cues are integral for successful performance.

128 Norman (2005) demonstrated that the greater and more diverse an expert’s memory
129 for patterns, the faster their capacity to match a visual percept against a stored pattern. For
130 example, a pathologist reviewing a breast biopsy slide might associate the destruction of
131 normal, lobular architecture of the breast glands (feature) with the likelihood of cancer
132 (event). As additional cases are reviewed, a repertoire of feature-event associations is
133 accrued, enabling more precise discrimination in future encounters. As these associations
134 become integrated to form patterns, cognitive processes become automated, reducing the
135 demand on cognitive resources, including working memory, while maintaining accuracy and
136 efficiency (e.g., see Curby & Gauthier, 2007; Curby et al., 2009 for evidence of domain-
137 specific visual working memory capabilities afforded by expertise).

138 Indirect evidence of the role of cue utilization in supporting diagnostic performance
139 is evident in experts’ extraction of a limited number of diagnostic features and their relatively
140 rapid and efficient formulation of diagnoses in comparison to non-experts (e.g., Brennan et
141 al., 2018; Carrigan et al., 2019; Carrigan et al., 2018; Evans et al., 2013; Krupinski et al.,

142 2013; Kundel & La Follete, 1972). However, the strength of these associations in memory is
143 likely to depend on the frequency with which they are activated. For example, patterns of
144 features that are reviewed less frequently in practice may decay through inactivity, while a
145 lack of exposure to specific cases may result in patterns of features that are imprecise and/or
146 liable to inappropriate activation, resulting in diagnostic errors. Since the activation of
147 patterns is reliant upon cues in memory, differences in the capacity to utilize cues within a
148 given context is likely to be an important cause of differences in diagnostic accuracy.

149 Ideally, assessments of cue-based associations in memory would involve the
150 identification of a universal catalogue of features that could constitute a benchmark for a ‘test
151 of existence’. However, the specific feature-event associations that experts acquire are shaped
152 by their individual experience. Moreover, visual features may be more or less salient based
153 on individual differences in visual detection skills, so that, despite similar levels of
154 experience, experts are unlikely to share identical cue-based relationships in memory.

155 Despite differences in the specific feature-event/object relationships in memory, it
156 remains possible for practitioners to achieve similar levels of performance, particularly in the
157 context of diagnosis. Characterizing the nature of this behavior allows more general
158 inferences to be drawn concerning the application or utilization of cue-based associations
159 from memory. Relatively higher cue utilization can be inferred based on the capacity of a
160 practitioner to: (1) rapidly identify areas of concern, (2) accurately recognize classes or
161 categories of features, (3) greater and more rapidly differentiate associations between
162 features, (4) discriminate relevant from less relevant features during problem-solving, and (5)
163 demonstrate a more explicit prioritization of the acquisition of features during problem
164 orientation (Wiggins, 2014; 2020).

165 Comparative behavioral assessments of cue utilization have successfully
166 differentiated diagnostic performance across a range of non-medical contexts including rail

167 control (Sturman et al., 2019), aviation piloting (Wiggins et al., 2014; Schriver et al., 2008),
168 air-traffic control (Falkland & Wiggins, 2019), water safety (Wiggins et al., 2019), software
169 engineering (Loveday et al., 2014), and electricity network power system control (Loveday et
170 al., 2013a). In medical domains, including radiology, (Carrigan et al., 2020), paediatrics
171 (Loveday et al., 2013b), and anaesthesiology (Crane et al., 2018), behaviour reflecting higher
172 cue utilization is associated with greater levels of accuracy in both direct and indirect
173 measures of diagnostic performance.

174 The primary goal of the present study was to test the contribution of cue utilization in
175 the diagnostic performance of histopathologists, accounting for self-reported experience. In
176 the case of histopathology, diagnosis requires that a clinician match features associated with a
177 pattern of cells against a repertoire of features in memory. These features include tissue
178 architecture, cell arrangement, cytoplasmic and nuclear shape, size, colour and density.

179 A greater and more discriminating repertoire of feature-event associations, reflecting
180 a greater capacity for the utilization of cues, is likely to enable a more accurate and rapid
181 diagnosis. Therefore, it was hypothesized that relatively higher cue utilization in the context
182 of histopathology would be associated with relatively greater accuracy on a simulated
183 diagnostic task, independent of experience.

184 185 **METHOD**

186 187 **Participants**

188 Pilot data were collected from eight histopathologists across a range of experience.
189 Experimental data were then collected from 54 participants (32 female) who participated in a
190 conference setting ($n = 35$), or online ($n = 19$) and who were familiar with reporting
191 histopathological specimens. The mean age of histopathologists in the experimental group
192 was 46 years ($SD = 12$ years). Forty participants were qualified pathologists and 14 were
193 residents (pathologists in training). Participants reported an average experience as a

194 pathologist of 14 years ($SD = 12$, range 1-52), having recently read between zero (one was
195 retired) to 14000 cases per year ($M = 3663$, $SD = 3554$). Three participants were left-handed,
196 all reported normal or corrected-to-normal vision, and all were naïve to the purposes of the
197 experiment. In return for participation, participants were offered the chance to win an iPad.
198 The study was approved by Macquarie University Human Research Ethics Committee
199 (Medical Sciences).

200

201 **Measures**

202 The participants completed a 45-min task which included: (1) a demographic survey,
203 (2) an assessment of cue utilization using the Expert Intensive Skills Evaluation platform
204 (EXPERTise 2.0; Wiggins et al., 2015), and (3) a computer-based static image recognition
205 task that provided an independent measure of diagnostic performance.

206

207 **(1) Demographic Survey: Covariates**

208 The participants were asked to indicate their age, sex, handedness, qualifications, their
209 number of years of experience in pathology, the number of cases performed per day, the
210 number of cases performed per year, and how frequently they played video games or a
211 musical instrument. If they played a musical instrument, they were asked to indicate their
212 perceived level of proficiency. These data were recorded, as there is evidence to suggest that
213 video game players perform at a higher level on attentional tasks (e.g., Cain et al., 2014), and
214 that playing a musical instrument may enhance visuo-spatial abilities (Tanner Boyd et al.,
215 2008). Using five-point Likert scales, participants were also asked about their energy levels
216 at time of experimentation, their confidence in their role, the extent to which they considered
217 that ‘pattern recognition is an inherent skill which cannot be taught’, and their self-rated
218 performance as a pathologist.

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(2) Cue utilization

Cue utilization was assessed using the Expert Intensive Skills Evaluation platform (EXPERTise 2.0; Wiggins et al., 2015). EXPERTise 2.0. is an online assessment tool that incorporates five tasks that are designed to assess behaviour that corresponds to the utilisation of cues in a specific domain. Guided by subject-matter experts, stimuli are developed for the various tasks that represent a specific domain or context.

In the Feature Identification Task (FIT), participants are asked to identify, as quickly as possible, an abnormality or area of concern. Participants responded to one practice and 15 randomised trials, 10 of which incorporated a single area of abnormality while the remainder were normal. The anatomical location of the abnormal images comprised the breast (2), lung (2), gastrointestinal tract (4), liver (2) and salivary gland (1). The response was made under free-viewing conditions and no feedback was provided. Notably, no assumptions are made about what specific features experts should use to select a region. In the FIT, higher cue utilisation is generally associated with lower mean response latency, reflecting the rapid and targeted identification of an area, rather than an exhaustive search (Loveday et al., 2013a) (See Figure 1).

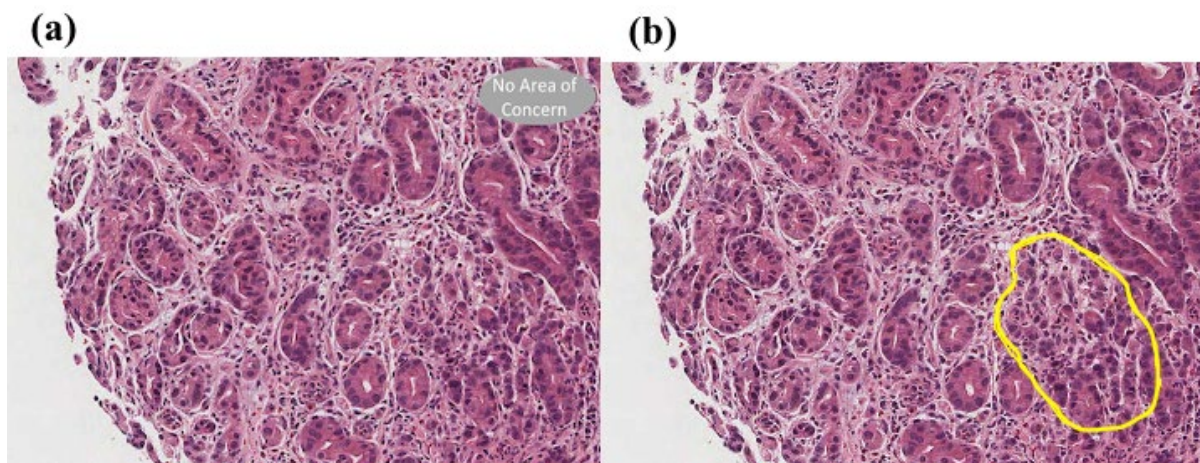


Figure 1: Exemplar image from the first of five tasks (the Feature Identification Task) from the Pathology edition of EXPERTise 2.0. Panel (a) depicts an image presented to the participants. Panel (b) depicts the image with the abnormal area outlined in yellow, representing gastric adenocarcinoma.

239 In the Feature Recognition Task (FRT), participants are asked to classify stimuli
240 following a short exposure. One practice and 20 randomized, experimental scenarios were
241 displayed for four seconds. Each scenario contained an abnormality, in response to which,
242 participants were asked to select one from five multiple choice options to categorise the
243 abnormality (Benign Neoplasm, Malignant Neoplasm, Reactive/Inflammatory Process,
244 Developmental, Metabolic). No feedback was provided. In the FRT, higher cue utilization is
245 generally associated with greater accuracy (Wiggins & O'Hare, 2003).

246 In the Feature Association Task (FAT), participants are asked to assess the relatedness
247 of pairs of pathological, text-based, task-related stimuli using a six-point Likert Scale. The
248 relatedness of the texts within each trial varied and was reviewed by a subject matter expert.
249 Over one practice trial and 15 randomized experimental trials, the two terms were presented
250 sequentially for 1500ms after which participants were asked to rate the relatedness of the

251 features on a six-point Likert scale (from 1 = 'Extremely unrelated' to 6 = 'Extremely
252 related'). For example, 'Granulation Tissue' (feature) might be followed by 'Tuberculosis'
253 (event). Seven pairs were less likely to be related, (e.g., 'Amyloid' (feature) followed by
254 'Grass' (event) and 8 were more likely to be related in practice (e.g., 'Bubbly Cytoplasm'
255 (feature) followed by 'Chordoma' (event)). In the FAT, higher cue utilisation is typically
256 associated with greater variance in the perceived relatedness of the terms as a function of
257 response latency (Morrison et al., 2013).

258 In the Feature Discrimination Task (FDT), participants are presented with a short,
259 written description of a problem-oriented scenario. On the basis of this information, they are
260 asked to select a response from four possible options based on their typical response (i.e.,
261 'What would be your first response in this situation?'). Having selected a response,
262 participants are presented with a list of features that were incorporated in the scenario and are
263 asked to rate, with reference to the decision, the perceived importance of the features using a
264 10-point Likert scale (from 1 = 'Not important at all' to 10 = 'Extremely important'). In the
265 FDT, higher cue utilization is associated with greater variance across feature-relevance
266 ratings (Weiss & Shanteau 2003; Pauley et al., 2009), where participants are more likely to
267 select either 'Not important at all' (1) or 'Extremely important'(10).

268 For the Feature Prioritization task (FPT), participants are required to prioritise
269 information to solve a histopathology-related problem. The histopathologists were presented
270 with incomplete, descriptive scenarios ('You are doing routine reporting. As quickly as
271 possible, access the information below that you feel is necessary to decide on your
272 response. '), and were provided a list of 14 information screens (feature cues), varying in
273 relevance and presented randomly in drop-down tabs from which feature-related information
274 could be accessed (e.g., 'Clinical Impression', 'Low power microscopic image'). Participants
275 with higher cue utilisation tend to access the information in a less sequential manner,

276 reflecting their ability to prioritize the information perceived as important to their goal.
 277 Meanwhile, participants with lower levels of cue utilisation tend to access the sub-menus in a
 278 more sequential manner, accessing features as they are listed (Wiggins & O’Hare, 1995).
 279 Higher cue utilization is associated with a lower frequency of pairs of features accessed in
 280 sequence, calculated as a proportion of the total frequency of pairs of features accessed
 281 during the scenario (Wiggins & O’Hare, 1995) (see Table 1).

282

283 **Table 1:** Summary of five tasks within EXPERTise 2.0.

<i>Task</i>	<i>Cognitive Process Examined</i>	<i>Task Description</i>	<i>Measure</i>	<i>Validity/Reliability</i>
284 FIT	Identification of predictive features	Identify, as quickly as possible the area of concern.	Response latency	Loveday et al. (2013) Wiggins, Brouwers, Davies, and Loveday (2014)
FRT	Identification of predictive features	Select the category of abnormality, displayed for four seconds.	Accuracy	Loveday et al. (2013)
FAT	Feature-event relationships in memory	Rate the strength of perceived associations between the feature-event	Variance divided by response latency	Morrison, Wiggins, Bond, and Tyler (2013)
FDT	Discrimination between predictive features	Rate the relative importance of features during a task-related problem-solving process.	Variance	Pauley, O’Hare, and Wiggins (2009)
FPT	Prioritization of feature-event relationships	Acquire task-related information to solve a problem-solving process.	Ratio of sequential to non-sequential menus accessed	Wiggins and O’Hare (1995) Wiggins, Stevens, Howard, Henley, and O’Hare (2002)

285 Note: EXPERTise = EXPERT Intensive Skills Evaluation; FIT = feature identification task;
 286 FRT = feature recognition task; FAT = feature association task; FDT = feature discrimination
 287 task; FPT = feature prioritization task.
 288

289 The test-retest reliability of each of the tasks that comprise EXPERTise 2.0 has been
290 demonstrated in the context of audiology (Watkinson et al., 2018), while test-test reliability
291 of classifications based on performance aggregated across the five tasks has been
292 demonstrated in the context of electrical transmission power control (Loveday et al., 2013).
293 The construct validity of the EXPERTise 2.0 classifications has been demonstrated in
294 radiology (Carrigan et al., 2020), transmission and distribution power control (Loveday et al.,
295 2013a; Sturman et al., 2019), software engineering (Loveday et al., 2014), and aviation
296 (Wiggins et al., 2014), while predictive validity has been demonstrated in audiology
297 (Watkinson et al., 2018).

298

299 **(3) Diagnostic Performance**

300 Diagnostic performance was assessed using a static image recognition task. The
301 stimuli consisted of one practice and 31 test images from various anatomical locations (e.g.,
302 breast, kidney, skin). Each image included five unique multiple-choice responses developed
303 by two subject matter experts. Four of the images demonstrated pathologies not included in
304 the multiple-choice options, where the correct answer was ‘none of the above’. The
305 participants were instructed: ‘As quickly as possible, please select the most correct answer
306 from the options below.’ The de-identified, images were provided by the subject matter
307 experts (See Figure 2).

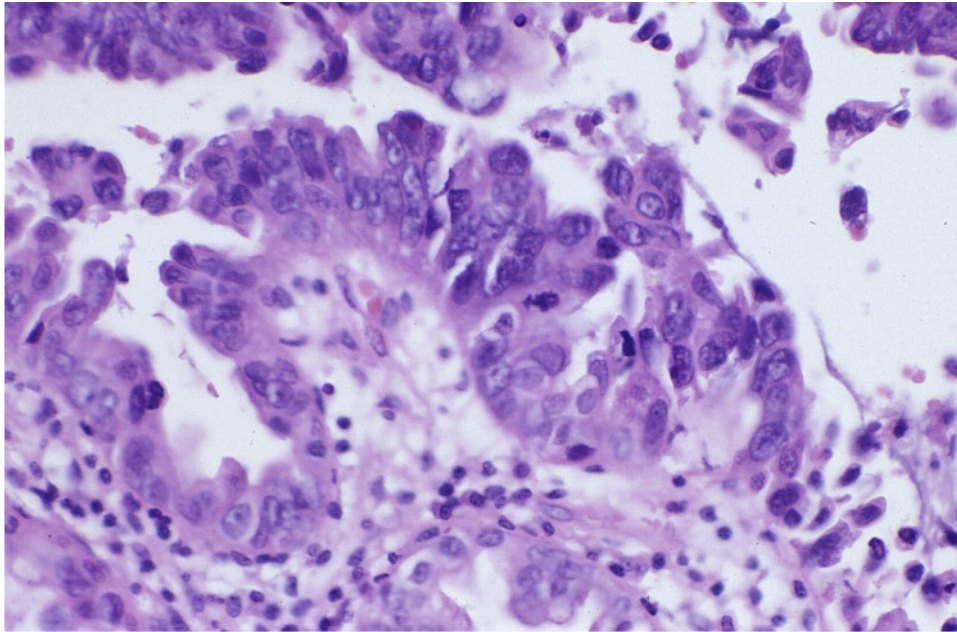
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The Mucosal epithelium of this gallbladder shows:

- a) Hyperplasia
- b) Viral infection
- c) Carcinoma in situ
- d) Chronic cholecystitis
- e) None of the above

Figure 2: Exemplar of an image from the static image recognition stimuli set.

Answer = 'c'.

313

314 **Procedure**

315 The research was conducted in accordance with the American Psychological
316 Association Code of Ethics and was approved by Macquarie University Human Research
317 Ethics Committee. Informed consent was obtained from all participants. EXPERTise 2.0 and
318 the static image recognition tasks were counterbalanced across participants. All of the tasks
319 within EXPERTise 2.0 were blocked in a set order and the scenarios were randomized within
320 task. After completing a series of demographic questions, each task began with a practice
321 trial followed by the EXPERTise 2.0 or static image recognition tasks.

322

323

324 **Results**

325 **Preliminary Analysis**

326 All statistical analyses were performed using IBM Statistical Software for the Social
327 Sciences (SPSS Version 25). Outliers defined as +/- 2 SD were removed from the
328 EXPERTise raw data (4 participants) leaving 50 participants for the main analysis. As the
329 participants' raw scores for each of the five EXPERTise 2.0 tasks were on different scales,
330 these were standardized (z scores) and then aggregated across the five tasks. The dependent
331 variable for the image interpretation task was accuracy (% correct).

332 Nineteen participants completed the study online at their convenience. The study
333 instructions included requests to perform the study on a laptop or desktop (no tablets or cell
334 phones), and at a time when they were least likely to be interrupted. An independent samples
335 *t*-test was performed and showed no differences in performance between those participants
336 who completed the study in a conference setting or online; $t(52) = -0.3, p = .77$.

337

338 **1) Demographic Survey: Covariates**

339 A series of correlations were conducted between the demographic variables and
340 accuracy on the static image recognition task. As expected, positive Pearson's correlations
341 were evident between accuracy on the static image recognition task and both the number of
342 cases performed per day; $r(52) = .39, p = .004$, and the number of cases performed per year;
343 $r(52) = .37, p = .006$. This suggests that the diagnostic performance measure has construct
344 validity. A positive Spearman's correlation was evident between self-rated confidence in
345 their role as a pathologist and performance on the image interpretation task; $r_s(52) = .34, p =$
346 $.01$. There was no correlation between self-reported years of experience and performance on
347 the static image recognition task; $r(52) = .23, p = .097$. There were no other statistically
348 significant correlations evident ($p > .05$). Since level of confidence is a subjective measure, it

349 was not included in the main analysis. As the number of cases/day and per year are
350 essentially the same measure, only the number of cases per year was included as a potential
351 explanatory variable (covariate) in the main analysis.

352

353 **(2) Cue utilization**

354 Cue utilization was established based on the participant's performance across the five
355 tasks included in EXPERTise 2.0. Previous research involving the five EXPERTise tasks
356 suggests that performance can be discriminated at two levels (higher, lower) that reflect
357 differences in behaviour during tasks that demand the utilization of cues (e.g., Brouwers et
358 al., 2017; Carrigan et al., 2020; Falkland & Wiggins, 2019). Consequently, a *k*-means cluster
359 analysis was employed to delineate two groups based on the standardised scores for the five
360 EXPERTise tasks.

361 An inspection of the centroids that emerged following the cluster analysis was used to
362 distinguish higher from lower performance and ensure that this pattern was uniform across
363 the five tasks. Consistent with the hypothesis, the cluster analysis in the present study
364 reflected uniformly, a pattern of centroids that distinguished higher from lower performance.
365 In comparison to lower cue utilization, higher cue utilization is characterized by faster
366 responses in the FIT, greater accuracy in the FRT, greater variance as a proportion of
367 response latency in the FAT, greater variance in the FDT and a lower proportion of features
368 accessed in the sequence in which they were presented in the FPT.

369 Eighteen participants comprised a group whose behavior was consistent with lower
370 cue utilization, while 32 participants comprised a group whose behavior reflected higher cue
371 utilization (see Table 2). This delineation is intended to take into account non-linear changes
372 that occur in the rate at which cue-based associations are identified and retained in memory.
373 There were proportionally more trainees assigned to the lower cue utilization group (see

374 Table 3). Four participants did not complete all of the EXPERTise 2.0 tasks, so were not
 375 assigned a cluster membership. Notably, cue utilization in this case, is a relative, not absolute,
 376 measure. Therefore, those participants assigned to Cluster 1 show patterns consistent with
 377 *relatively* lower cue utilization compared while those participants assigned to Cluster 2
 378 showed patterns consistent with *relatively* higher cue utilization.

379

380 **Table 2:** Centroids for the standardized scores for each of the EXPERTise 2.0 five tasks
 381 distributed across the two groups that were delineated by a *k*-means cluster analysis.

	Cluster 1: Lower Cue Utilization Group (<i>n</i> = 18)	Cluster 2: Higher Cue Utilization Group (<i>n</i> = 32)
<i>Task</i>	<i>Centroid</i>	<i>Centroid</i>
Feature Identification	.92616	-.51780
Feature Recognition	-.80742	.50503
Feature Association	-.72342	.39166
Feature Discrimination	-.11779	.11648
Feature Prioritization	.23245	-.06519

382 **Table 3:** Frequency of trainee and qualified pathologists per cluster group.

	Cluster 1: Lower Cue Utilization Group (<i>n</i> =18)	Cluster 2: Higher Cue Utilization Group (<i>n</i> =32)
Trainees	7	4
Qualified	11	28

383

384 **(3) Diagnostic performance**

385 Diagnostic performance was measured as percentage accuracy on the static image
386 recognition task; Mean accuracy = 66.55% ($SD = 12.4$). Single-sample t -tests on mean
387 accuracy relative to chance, where chance was 20% (1 in 5 possible responses), showed that
388 pathologists performed above chance on the image interpretation task; $t(53) = 27.59, p <$
389 $.0001$.

390 To address our first aim, a between-groups analysis of covariance (ANCOVA) was
391 performed, incorporating two levels of cue utilization (higher/lower) as the independent
392 variable, and the number of cases per year included as a covariate, to test its contribution to
393 diagnostic performance; $F(1,47) = 8.4, p = .006, \eta_p^2 = .14$. ¹An inspection of the means
394 indicated that, controlling for cases per year, those histopathologists with higher cue
395 utilization ($M = 71.57, SD = 9.21$) performed more accurately on the static image recognition
396 task compared to pathologists with lower cue utilization ($M = 60.93, SD = 13.32$) (see Figure
397 3).

¹ As the sample sizes in the cue utilisation groups were unequal, a Levene's test of equality was performed, comparing the two categories of cue utilisation on diagnostic performance, $F(48) = 3.36, p = .073$. This suggests that equal variances can be assumed.

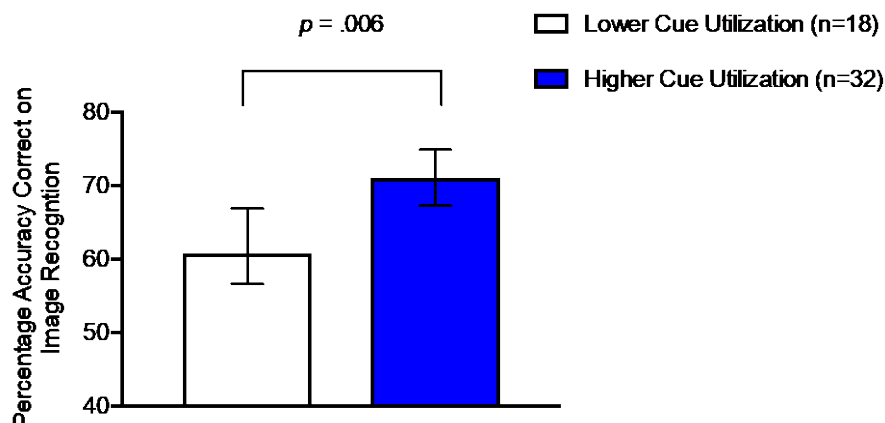


Figure 3: Percentage accuracy mean scores on the static image recognition task, distributed across cue utilization, controlling for cases read per year, for fifty histopathologists. Error bars represent 95% confidence intervals. Note: Chance is 20%.

399 An independent samples *t*-test, incorporating cue utilization as the grouping variable,
 400 failed to reveal a statistically significant difference between the groups in the number of cases
 401 read per year, $t(48) = -1.7, p = .1$. This suggests that cue utilization and cases per year read by
 402 pathologists contribute independently to the difference in performance on the diagnostic task.

403 Although the histopathologists performed above chance on the static image
 404 recognition task, their performance as a group was far from ceiling ($M = 66.55\%$). It is
 405 possible that these results reflect that the sample included pathologists in training (14/40)
 406 who are yet to become familiar with the pathologies included in the test set. Alternatively,
 407 while the stimuli were carefully selected by two subject matter experts, it may be the case
 408 that the performance of participants reflects the inherent variability in real-world images, and
 409 possibly within the image set. These factors include the difference in prevalence of specific
 410 types of cases in different practice settings.

411 In a post hoc, exploratory analysis, we first tested whether disease frequency and the
 412 rate at which histopathologists were likely to have encountered similar cases previously in

413 their practice, may be related to their performance on the static image recognition task. Of the
414 cases in the set, 12/31 cases were classified by a subject matter expert, and cross checked
415 with available epidemiology data, as ‘rare’, while 19 of the 31 cases were considered
416 ‘common’. The case with the lowest accuracy across the cohort was a rarely encountered
417 disease occurring in a skin biopsy specimen, where six of the 50 pathologists (5/6 with higher
418 cue utilization and 1/6 with lower cue utilization) diagnosed the case accurately. For this
419 condition, there is a possibility that the low accuracy resulted from the relative unfamiliarity
420 of the case.

421 A mixed-repeated ANCOVA testing the accuracy data from the static image
422 recognition task, with disease frequency (common/rare) as a within-subjects variable, cue
423 utilization (higher/lower) comprising a between-subjects variable, and the number of cases
424 per year as a covariate, revealed a main effect for disease frequency, $F(1,47) = 66.30, p <$
425 $.0001, \eta_p^2 = .59$. An inspection of the means indicated that, consistent with expectations,
426 accuracy was greater for cases that were classified as common ($M = 74.60, SD = 11.29$)
427 rather than rare ($M = 53.50, SD = 15.9$).

428 A main effect was also evident for cue utilization, $F(1,47) = 8.1, p = .007, \eta_p^2 = .15$,
429 and an inspection of the means revealed that those participants with higher cue utilization
430 recorded greater accuracy for both the more common cases ($M = 78.84, SD = 13.65$) and the
431 rarer cases ($M = 58.85, SD = 19.23$) compared to histopathologists with lower cue utilization
432 (common: $M = 70.37, SD = 18.3$; rare: $M = 48.16, SD = 25.81$), controlling for the number of
433 cases per year (see Figure 4).

434

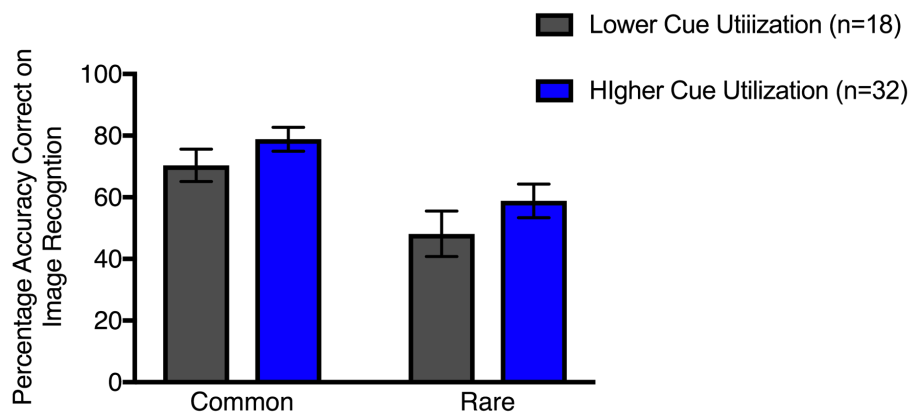


Figure 4: Percentage accuracy mean scores on the static image recognition task distributed across cue utilization, for the common and rare cases, controlling for cases read per year, for fifty histopathologists. Error bars represent 95% confidence intervals.

435 For a small number of images (4), the correct response was ‘none of the above’, since
436 the pathology depicted was not listed as one of the other alternatives. Therefore, we explored
437 whether the relationship between cue utilization and accuracy differed, depending upon the
438 presence or absence of a pathology listed as an alternative. A mixed-repeated ANCOVA,
439 incorporating two levels of cue utilization as a between-subjects factor (higher/ lower) and
440 the presence or absence of a listed pathology as a within-groups variable, tested whether there
441 were differences in the accuracy of responses. The estimated number of cases read per year
442 was employed as a covariate in the analysis.

443 The results revealed a statistically significant interaction between cue utilization and
444 the presence or absence of a listed pathology, $F(1,47) = 7.42, p = .009, \eta_p^2 = .14$. Post hoc
445 contrasts (Bonferroni corrected) indicated that those participants with lower cue utilization
446 ($M = 52.54, SD = 38.53$) were more likely to record a false positive, rather than correctly
447 respond with ‘none of the above’, compared to those participants with higher cue utilization

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448 ($M = 79.04$, $SD = 28.7$) (Note: this analysis is exploratory, as there was a disproportionate
449 number of not-listed cases (4) compared with the listed cases (27) (see Figure 5).

450

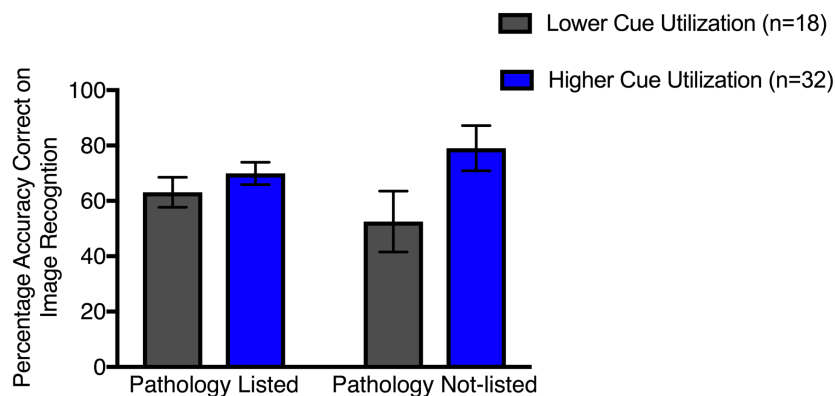


Figure 5: Percentage mean scores on the static image recognition task, distributed across cue utilization, for the pathology listed and not-listed cases, controlling for cases read per year, for fifty histopathologists. Error bars represent 95% confidence intervals.

451 In combination, the data suggest that differences in cue utilization contribute to
452 performance on a diagnostic task, over and above the estimated number of cases read per
453 year, and that these results may in part, be driven by disease prevalence both in our image set,
454 and epidemiologically, along with the ability to recognize when a pathology is present or not
455 present in an image.

456

457 Discussion

458 The overall aim of this study was to investigate whether diagnostic assessments of cue
459 utilization differentiate performance in the context of histopathology, accounting for self-
460 reported experience (number of pathology cases interpreted per year). Consistent with the
461 hypothesis, higher cue utilization was associated with greater accuracy on a simulated
462 diagnostic interpretation task requiring evaluation of tissue with significant abnormalities. A

463 positive relationship was also evident between the estimated number of cases read per year
464 and diagnostic accuracy. However, no relationship was evident between the estimated
465 number of cases read per year and cue utilization. Consistent with previous research, this
466 suggests that cue utilization and experience, in the form of the self-reported estimates of the
467 number of cases read per year, contribute independently to diagnostic accuracy (Carrigan et
468 al., 2020; Crane et al., 2018; Loveday et al., 2013b, Sturman et al., 2019).

469 This study provides evidence for differences on diagnostic performance based on cue
470 utilization, independent of the number of cases read per year. However, there are other
471 factors to consider that also contribute to expertise, including personality, genetic and
472 developmental factors (Hambrick et al., 2016), that were not evaluated in the current study.
473 Further, there is evidence to suggest that some pathologists have an inherent domain-general
474 ability for visual recognition, independent of experience (e.g., Trueblood et al., 2018). It is
475 also likely that in practice, if the disease frequency was inconsistent, 'experience' would
476 begin to affect diagnostic outcomes and accuracy, independent of the number of cases read
477 per year. Future research examining these issues is warranted, particularly comparing
478 extreme values of cue utilization, where differences and variability in performance across the
479 tasks can be maximized, and equal sample sizes can be assured. Importantly, the findings in
480 the present study are consistent with Carrigan et al. (2020) who showed that among
481 radiologists, cue utilization was positively associated with performance on a diagnostic task,
482 independent of experience.

483 Although performance on the diagnostic task was above chance, it should be noted
484 that overall accuracy was 66.55%. This is unsurprising as none of the participants reported
485 being accustomed to diagnostic reporting from histopathology images on screens. The
486 simulated diagnostic task presented a target tissue abnormality in a setting that was
487 unfamiliar, rather than the normal pathological examination using an optical to view multiple

488 fields at multiple magnifications. Although many laboratories are moving from optical
489 microscopy to digital whole slide images, this was not the case for the current sample.
490 Furthermore, the experimental setting lacked the opportunity for corroboration from
491 colleagues or other resources such as text books or online images that would normally be
492 available in routine practice when diagnostic uncertainty is encountered. Although presenting
493 its own challenges, our diagnostic setting reproduces the essence of the routine practice
494 setting. Unfortunately, the routine practice setting is not yet amenable to the study of
495 activation of highly-refined cue-based associations in memory and how these associations are
496 able to better discriminate differences in capability.

497 The post hoc analysis suggested that the types of cases and the prevalence of cases to
498 which pathologists are exposed may be associated with differences in accuracy. Specifically,
499 in comparison to participants with lower cue utilization, participants with higher cue
500 utilization demonstrated relatively greater accuracy for less common pathologies, and where
501 the pathology was not listed as a specific option for selection (i.e., the correct option was
502 ‘none of the above’). This has important training implications given that discordance errors
503 are higher for histopathologists who interpret lower weekly case volumes, worked in smaller
504 practices or non-academic settings.

505 Since improvements in cue utilization are thought to occur through the internalization
506 of feature-event associations in memory, learning opportunities are necessary that enable, as
507 quickly as possible, the extraction of features and their association with specific pathologies
508 in memory are necessary (Wiggins, 2014). In the absence of supervised operational exposure,
509 structured simulation such as reviewing and testing using image libraries with feedback,
510 offers an alternative with the potential to facilitate the acquisition of cue-based associations at
511 a rate faster and more efficiently than might be afforded through work-based exposure. With

512 further research, evaluations based on normative assessments of performance could be
513 employed to ensure successive improvements in cue utilisation.

514 Opportunities for future research also lie in examining whether cue utilization
515 moderates performance differently depending upon the prevalence of cases. In the current
516 study, our exploratory findings suggested that disease frequency or prevalence was related to
517 diagnostic performance. Low target prevalence (i.e., rare or uncommon targets, few cases are
518 truly abnormal) generally results in elevated miss rates (Evans et al., 2011; Mitroff & Biggs,
519 2014; Wolfe et al., 2005). Evans et al. (2011) demonstrated this ‘low prevalence effect’ in a
520 cytology screening context where in the United States, the epidemiological prevalence of
521 cervical cancer is around 1% (Benard et al., 2004). By contrast, disease prevalence in the
522 context of histopathology tends to be higher.

523 Typically, in a breast histopathology setting, prior to the evaluation by a
524 histopathologist, the patient and tissue samples have already been subjected to diagnostic
525 testing and procedures such as mammograms, Prostate Specific Antigen (PSA) testing for
526 prostate cancer, polyps biopsied during routine colonoscopies, or surgical excision. Further,
527 specimens are accompanied by clinical information and surgical reports. This is likely to
528 create an environment that potentially primes the confirmation of an abnormality. Testing the
529 existence of ‘abnormality priming’ is necessary to consider the effects of prevalence on
530 pathologists’ cue utilization on a longer-term basis.

531

532 **Conclusion**

533 This study was designed to test the role of cue utilization in the diagnostic
534 performance of histopathologists. Accounting for the self-reported number of cases reported
535 per year, higher cue utilization was associated with higher accuracy on an independent,
536 simulated diagnostic task. This effect was greatest where the pathology depicted on the image

537 was not listed as a potential classification option and ‘none of the above’ was the accurate
538 response.

539 Despite the limitations associated with the use of a simulated task that potentially
540 lacks ecological validity, the results raise important issues concerning the relationship
541 between motivation and cue utilization, particularly in response to challenging tasks. The
542 outcomes also highlight the value of an approach that does not assume that experts use the
543 same cues or features during problem-resolution. Our exploratory image analyses showed
544 that factors such as disease prevalence are also likely to influence accuracy. Crucially, the
545 outcomes of the study have important implications for the development and maintenance of
546 skills amongst pathologists: Exposure sufficient to acquire and utilize cue-based strategies
547 appears to be associated with the highest level of performance on the diagnostic task.

548

549 **Key Points**

- 550 • In pathology, accurate diagnosis involves accurate, reliable and timely responses.
- 551 • Pathological cue utilization is positively associated with performance on a diagnostic
552 task, independent of the number of cases reported per year.
- 553 • A post hoc analysis suggested that higher cue utilisation may be associated with a
554 greater capacity to recognise rarer and low prevalence cases.
- 555 • Targeted training that encourages the acquisition and utilization of cue-based
556 strategies is recommended.

557

558 **ORCID iD**

559 Ann J. Carrigan <https://orcid.org/0000-0002-2525-9241>

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561

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- 721
722 Ann J. Carrigan is a postdoctoral researcher at Macquarie University and works in radiology
723 as a medical sonographer. Her research focuses on medical image perception and expertise in
724 diagnostic medicine.
- 725
726 Amanda Charlton is an Anatomical Pathologist at Auckland City Hospital, her clinical work
727 involves making diagnoses on tissue biopsies. Her interests include image perception,
728 medical education, artificial intelligence and bias in diagnostic pathology.
- 729
730 Elliott Foucar, MD is an Adjunct Professor in the Department of Pathology, University of
731 New Mexico School of Medicine. His major areas of interest are general diagnostic surgical
732 pathology, dermatopathology, cytopathology, and autopsy pathology.
- 733

Cue based strategies in pathology

734 Mark W. Wiggins is a professor of organizational psychology at Macquarie University. His
735 research focuses on skill acquisition and expertise in advanced technology
736 environments.

737

738 Andrew Georgiou is a professor of Diagnostic Informatics at Macquarie University. His
739 research focuses on diagnostic and organizational communication within the healthcare
740 system.

741

742 Thomas J. Palmeri is a professor of psychology, ophthalmology, and visual sciences at
743 Vanderbilt University. His research focuses on perceptual categorization, category learning,
744 visual learning, visual memory, perceptual expertise, object and face recognition,
745 automaticity, perceptual decision making, mathematical, computational, and neural
746 modelling.

747

748 Kim M. Curby is an associate professor of cognitive psychology at Macquarie University.
749 Her research focuses on the cognitive mechanisms and neural substrates that underlie expert
750 performance in visually based domains.

751

752