Perceptual Expertise in Fingerprint Classification

Anneliese Cavallaro

The Univeristy of Adelaide

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Table of Contents

List of Tables and Figures

Figures

Abstract

Fingerprint examiners classify crime scene prints as belonging a left or right hand and to a finger-type – thumb index, middle, ring or little – to help narrow their search for known candidate prints. While fingerprint examiners have been found to have impressive perceptual expertise little in known about their perceptual abilities in this aspect of the fingerprint examination process. The present study served as a first test of fingerprint classification expertise, probing experienced (n = 30) and novice (n = 30) examiners in their ability to classify a controlled, fully rolled, set of prints by hand-type and finger-type in a 10-alternative forced-choice task. Using a yoked novice-expert design performance was measured at two levels of specificity: a coarse-grained level accounting for hand-type classifications (i.e. "left" versus "right"), and a fine-grained level accounting for finger-type classifications (i.e., "thumb", "index', "middle", "ring", "little"). The results revealed experienced fingerprint examiners were indeed sensitive to the type of hand a fingerprint originated from and were significantly better than novices at these classifications. The experts were also able to classify fingerprints by finger-type, performing significantly above chance. Novices, on the other hand, did not differ from chance at classifying fingerprints by finger-type. These expert-novice differences remained large, even when accounting for response times when classifying prints by hand and finger-type. These data suggest that fingerprint experts are able to generalise their highly specific perceptual expertise with fingerprint to coarser grained levels of analysis: moving from identity to hand and finger classification.

Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any University, and, to the best of my knowledge, this thesis contains no materials previously published except where due reference is made.

Signature

Anneliese Cavallaro

8th April 2019

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Introduction

1.1. An introduction to Forensic Science

Forensic science evidence—fingerprints, blood patterns, DNA, shoeprints, hair, handwriting, CCTV, firearms and tool marks—is used to help solve a range of important problems induldinq identifying suspects in criminal investigations but also identifying victims in major disasters, piecing together the events leading up to a major disastor (e.g. bush fires, bomings etc). The stakes of failing to identity people in all of these cases are high, for both the victims and families involved. However, the stakes of incorrectly identifying people are also high. DNA evidence in particular has played a pivotal role in the exonerations of hundreds of people in the United States (Innocence Project, 2018). Critically, these exonerations reveal that trusted forms of evidence that have been in longstanding use, including eyewitness testimony, confessions, and forensic science, are not infallible (Kassin, 2008; Luftus, 2018; Innocence Project, 2018). It is, therefore, crucial to consider and evaluate the nature and limits of forensic science evidence and forensic decision-making.

Key reports by the US National Research Council (here after NAS report) in 2009 and the US Presentident's Council of Advisors on Science and Technology (here after PCAST report) detail particular strategies to strengthen forensic evidence, and consider the available empirical evidence establishing the validity of several different forms of forensic science evidence. (National Research Council, 2009, pp. 116-117; President's Council of Advisors on Science and Technology, 2016). Few of the disciplines reviewed were regarded as "foundationally valid" in these reports, with many lacking empirical demonstrations of accuracy. However, one forensic discipline that has been the focus of a growing body of research into the nature of forensic decision-making is fingerprint examination. Fingerprints have been used as evidence in the criminal justice system for over a century (Thompson, et al., 2017, p. 43) and they are a commonly used biometric. Fingerprint examiners spend years training to discriminate prints from the same finger and those from different fingers 'by eye' (Searston & Tangen, 2017c), and they demonstrate hallmarks of genuine perceptual expertise (Thompson & Tangen, 2014; Searston & Tangen, 2017c; Searston & Tangen, 2017a; Tangen, Thompson, & McCarthy, 2011; Searston & Tangen, 2017b). Better understanding the nature of expertise in fingerprints could serve as model for investigating human perceptual abilities in other similar forensic disciplines that rely on human interpration of visual evidence (e.g., firearms, tool marks, shoe prints, hair, handwriting, blood patterns). The current project will focus on one aspect of the fingerprint examination process that we know little about: fingerprint classification.

1.2. Forensic Science and Human Decision-Making

Public perception of forensic science evidence has perhaps been shaped by popular television crime dramas, such as *CSI: Crime Scene Investigation*, and longform crime documentaries (Schweitzer & Saks, 2007; Holmgren & Fordham, 2011; Cole, 2013). The popularity of fictional crime-shows has led to a phenomenon termed the "CSI effect", where these shows are believed to leave people with an unrealistic or misleading impression of the collection and analysis of forensic evidence (Schweitzer & Saks, 2007; Holmgren & Fordham, 2011; Cole, 2013). Contrary to reality, these shows often depict forensic science as fully automated computer-based identification systems (Cole, 2013; Schweitzer & Saks, 2007). These fictional depictions of forensic science ignore the human examiner behind the computer, who visually interprets the evidence at hand and decides if the crime scene and candidate samples belong to the same source (National Research Council, 2009, pp. 113, 128; President's Council of Advisors on Science and Technology, 2016, pp. 25-27, 47-48). As such, a thorough understadning of the how humans make judgements and decicions in forensic science is necessary in supplying foundational validity to these disciplines. From here I turn to fingerprint examination which offers a unique testbed for decision making with a stimulus many of us have no genuine expereince with, bar havign them on our finger, but for which there are elite fingerprint experts for comparision.

Fingerprint examination takes place within the mind of the human fingerprint examiner (Tangen, 2013). Fingeprint examiners are relied on to interpret if two prints were left by the same finger or different fingers (Searston, Tangen, & Eva, 2016). This task requires examiners' to see through variation in how a particular print can be impressed at different times (e.g., changes in positioning, pressure, distortion, surface, persperation) to the complex visual information that persists across different instances—from the general flow or patterning of the ridges (sometimes classified as "loops," "arches," or "whorls"), to the specific features and minutiae. In most cases the prints are 'unfamiliar' to the examiner, unless they have encountered that particular person's fingerprints in their casework in the past (Searston & Tangen, 2017a).This unfamiliar aspect of fingerprint examination is analogous to identifying a person you've never met before from photographs of their face (Young & Burton, 2018). That is, even though examiners have a lot of experience looking at fingerprints, they have little experience looking at fingerprints from the particular finger.

Fingerprint examiners learn how fingerprints tend to look and vary with experience (Searston & Tangen, 2017b), much like other domains of perceptual expertise where categories vary naturally (Mervis & Rosch, 1981; Rosch & Mervis, 1975)**.** The accumulation of expereince is thought to result in perceptual expertise marked by increased accuacy, and often speed, of discrimiantion, often times accompanied by an ability to generalise, or transfer, knowledge to new exemplars from the same category (Tanaka, Curran, & Sheinberg, 2005; Wong, Palmeri, & Gauthier, 2009). With experience, it also becomes possible to make more finer-grained classifications of fingerprints (Searston & Tangen, 2017b), much like other visual categories. Fingerprints can be classified at more coarse-grained levels of specificity, such as “loop pattern,” “left hand,” “right thumb,” down to more fine-grained levels of specificity, such as “Smith’s left thumb” at the level of identity. The more specific the classifcation, the smaller the pool of candidate prints for examiners to sift through (National Research Council, 2009, p. 122; Champod & Ian W, 2001; Dror & Mnookin, 2010). The current project will explore the nature of fingerprint classification decisions at the levels of hand and finger type.

1.3. The Nature of Fingerprints and Automated Identification Systems

Feature comparison relies on their being observable and distinct information in a stimulus. For fingeprrints this detail comes from the pattern of hills and valleys termed “ridges”, on the pads of our hands and feet which formed during feotal development and run deep into the dermal layers of skin (Campbell, 2011, p. 43; Thompson, et al., 2017, p. 17). The patterns form a range of features which are thought to vary between individuals and include: overall ridge flow, ridge frequency, location, and position of singular points (core(s) and delta(s)), the type, direction and location of minutiae or the particular features in prints, ridge counts between minutiae, and the location of pores (Pankanti, Prabhakar, & Jain, 2002; Cole, 1999). Fingerprint examiners describe relying on these features as information to identify latent fingerprints lifted from a crime-scene to a known candidate print.

Fingerprint examiners often describe there examination process as involving an *analysis* of the featrures of a latent prints, *comaprison* of the latent with exemplar prints of known origin, either from a an AFIS generated list or from a suspect list, an *evalution* of the degree of similarity and dissimilarity in the prints, and *verification* of the conclusion by at least one other fingeprint examiner, termed ACE-V (Expert Working Group on Human Factors in Latent Prints Analysis, 2012, pp. 2-9; National Research Council, 2009, p. 137). Automated fingerprint identification systems are used as a part of the examination process to speed up the search for similar known candidate prints (Langenburg, Hall, & Rosemarie, 2015). These systems contain state or national databases of fingerprints, which have been collected during operational policing, such as a part of an arrest, or 10-print card, see Figure 1. Candidate prints are deliberately rolled and to allow for the detail in the print to be clear with minimal distortion. Indeed, the algorithms of an AFIS are able to identify fully rolled prints with other fully rolled prints with very high degree of accuracy (Meagher, Dvornychenko, & Garris, 2014; Langenburg, Hall, & Rosemarie, 2015).

However, unlike prints rolled for an arrest card, latent prints, due to the nature in which they come to be, are subject to a range of factors which affect the ability of an AFIS to identify them. Latents typically have less surface area, and hence less information, than rolled prints (Meagher, Dvornychenko, & Garris, 2014; Langenburg, Hall, & Rosemarie, 2015). There are also a range of factors affecting the quality of latent fingerprints, including: the surface they were left on, the type of transfer media (sweat, oil, blood), the pressure and movement during deposit; and the preservation technique (Meagher, Dvornychenko, & Garris, 2014; National Research Council, 2009, p. 137). Furthermore, some ridge patterns have been found to be more susceptible to distortion or elasticity in the appearance of the ridges. “Right slanted loops” are thought to be more elastic than “plain whorls”, for instance, as two common fingerprint pattern types (Fagert & Morris, 2015). As a result of this within-finger variation and distortion, AFIS algorthims do not run in “lights out” mode, where there is no human interaction, when searching latent impressions—these cases are left to human examiners. That is, human fingerprint examiners are increasingly working with more complex and degraded latents impressions as a result of advances in AFIS technology.

Figure 1. The "10-print card" of my supervisor taken with a live scan macchine, where a digital verson of prints are captured, as oppsed to hand-rolled prints which are inked onto paper. Only a part of the prints are displayed in this image.

1.4. Research on Fingerprint Expertise

Since the release of the NAS report in 2009 a body of research has examined visual perceptual abilities in fingerprints, providing some clues as to the nature of fingerprint examiners visual perceptual skills. In one study, fingerprint examiners and novices discriminated pairs of 'ground truth' prints, of which the researchers knew the origin allowing them to assess the accuracy of the discriminations (Tangen, Thompson, & McCarthy, 2011). The fingerprint examiners were able to distinguish matching and highly similar non-matching fingerprints far more accurately than novices and made very few errors. Cases where the prints were falsely declared as a match accounted less than 1% of examiners' decisions. In other work, fingerprint examiners have been shown to repeat around 90 per cent of their match and non-match decisions (Ulery B. T., Hicklin, Buscaglia, & Roberts, 2012). Fingerprints examiners have also demonstrated a tendency to err on the side of caution, preferring to miss a correct identification when comparing prints, making more “no match” than “match” decisions irrespective of the ground truth— particularly for prints which were more difficult or highly similar (Tangen, Thompson, & McCarthy, 2011; Thompson, Tangen, & McCathy, 2014; Ulery B. T., Hicklin, Buscaglia, & Roberts, 2011; Ulery B. T., Hicklin, Buscaglia, & Roberts, 2012; Kellman, et al., 2014). One possible explanation for this conservatism is that examiners underestimate within-finger variation across different impressions left by the same finger (Thompson, et al., 2017). Others have suggested that this conservatism may reflect examiners accounting for the gravity of their decisions, with weight given to avoiding false identifications (Thompson, Tangen, & McCathy, 2013). However, verification of identification has been shown to significantly reduce the likelihood of falsely rejecting the true candidate (Ulery B. T., Hicklin, Buscaglia, & Roberts, 2011). Fingerprint examiners are exceptionally accurate, however, accuracy does not account for the decision making process itself.

Signal Detection Theory (SDT) has also been used to further describe the nature fingerprint discrimination decisions (Thompson, Tangen, & McCathy, 2013; Searston, Tangen, & Eva, 2016; Searston & Tangen, 2017a; Searston & Tangen, 2017b; Searston & Tangen, 2017c). In fingerprints ‘signal’ refers to prints left by the same finger, while ‘noise’ refers to prints left by different fingers. In a signal detection paradigm there are two ways of being right and two ways of being wrong. A print can be correctly declared a match (a hit), or correctly declared a non-match (a correct rejection). A print can also be falsely declared a match (a false alarm), or falsely declared a non-match (a miss). There are two measures of performance in a signal detection paradigm, discriminability or sensitivity and the level of the response criterion or response bias. Response criterion is characterised by the examiner’s bias towards making one kind of decision over the other— “match” or “no match”. A response of “match” to every pair of prints would be an extreme ‘liberal’ response bias in this context, while a response of “no match” to everything would be an extreme ‘conservative’ response bias (Phillips, Saks, & Peterson, 2001; Thompson, Tangen, & McCathy, 2013). Signal detection offers a means for research to examine peoples’ sensitivity to information in fingerprints, and other visual stimuli, that is diagnostic of their source.

Given examiners’ remarkable ability to discriminate fingerprints, a handful of studies have focused on better understanding the nature of this perceptual expertise: how do fingerprint examiners do what they do so? Novices, who have no formal training with fingerprints have been shown to perform well on a basic side-by-side fingerprint comparison task, but without highly similar distractor prints or highly similar non-matches (Vokey, Tangen, & Cole, 2009). Comparison of examiners with different levels of experience, has revealed that expertise offers an advantage in overall sensitivity. Thompson, Tangen and McCarthy (2014), set out to identify fingerprint expertise by testing the performance of experts, intermediate trainees, new trainees and novices. Their findings comparing across groups suggest a learning curve, where new trainees with six months or less training perform similarly to novices, while intermediate trainees, with an average of three and a half years of training, performed similarly to experts (Thompson, Tangen, & McCathy, 2014). Furthermore, when new trainees’ performance on a series of fingerprint and face tasks was tracked longitudinally over the first 12 months of training, their performance improved significantly over this time for fingerprints and not faces (Searston & Tangen, 2017b). These findings provide evidence for a domain specific improvement in perceptual skill with increased experience and formal training in fingerprint examination. Performance at the first stage of testing also predicted later performance, providing some evidence of stable individual differences from the outset of training (Searston & Tangen, 2017b). There is clear evidence that exposure to fingerprints contribute to increasing the ability to perceive their detail.

Research on the nature of fingerprint expertise, comparing experts and novices, also indicates that experts' superior performance remains under a variety of challenging examination conditions. Experts outperform novices at discriminating fingerprints when they are presented in noise, for less than half-second viewing time, and when the prints are inverted (Tangen, Thompson, & McCarthy, 2011; Thompson & Tangen, 2014; Searston & Tangen, 2017b). Moreover, experts' skills with fingerprints are not limited to fingerprint matching. Expert-novice differences have been observed using visual search tasks for fingerprint categorical information (i.e., searching for a loop or whorl fingerprint pattern) (Searston & Tangen, 2017a); and using a person discrimination task where examiners identify prints from different fingers of the same person (Searston & Tangen, 2017c). These findings suggest that the perceptual expertise examiners have developed may indeed generalise to broader level classifications of fingerprints, like hand and finger types.

1.5. Current Project

The computer algorithms used to help search state and national fingerprint databases return a list of the most highly similar prints to the latent recovered from a crime scene. However, these automated searches can result in long list of highly similar potential candidates for examiners to analyse. To help further narrow these lists of potential candidates when running latent fingerprints, fingerprint examiners can choose to nominate or classify the type of finger they think left the latent print: left or right little, ring, middle, index, and or thumb. An accurate hand and finger classification can potentially benefit the overall examination process by helping examiners to exclude more non-matches before the comparison stage and freeing up their time for other case work. Little is known about the nature and limits of this aspect of the fingerprint examination process. The current project is a first basic test of people's ability to classify fingerprints by hand and finger type.

The focus of this project is on hand and finger classification, operationally termed finger-nomination, as a part of fingerprint examination. Experts, with years of experience discriminating fingerprints, and novices, with no formal training in discriminating fingerprints, classify prints by hand and finger-type in a 10-alternative classification task. This first test will address two levels of finger classification. Firstly, exploring experts' and novices' accuracy, confidence and speed when deciding if a print belongs to a left or a right hand, averaging over the finger-type. And secondly, exploring experts' and novices' accuracy, confidence and speed when deciding if a print belongs to a little, ring, middle, index or thumb, averaging across hand-type. As there is no existing human performance data on fingerprint classification in the peer-reviewed literature, the primary goal is to gauge if people can classify fingerprints by hand and finger-type above chance and the extent to which examiners' experience and perceptual expertise with discriminating fingerprints offers an advantage. The broader goal of this research is to better understand the core components of perceptual expertise in fingerprints.

Previous research has established a human ability to detect visual information in fingerprints (Vokey, Tangen, & Cole, 2009). Furthermore, that years of experience offers an advantage in fingerprint discriminations (Tangen, Thompson, & McCarthy, 2011; Thompson & Tangen, 2014). More recent research has found that experienced fingerprint examiners can detect prints from different fingers of the same person (Searston & Tangen, 2017c). Fingerprint examiners can also detect different patterns of fingerprints in an array (e.g., “loop”, “whorl”, “arch”) more accurately than novices (Searston & Tangen, 2017a). On the basis of these findings, I anticipate that examiners' experience with prints, coupled with their specific use of hand and finger nomination judgements in operational contexts, will bring about superior fingerprint classification performance to novices. That is, if there is sufficient visual structure across different prints of the same finger type, or hand type, experts will be sensitive to it due to their experience with prints more broadly. Novices, on the other hand, bring no formal experience with fingerprints at the outset. Therefore, there classification ability provides an ideal baseline for comparison. Specifically, I predict the following pattern of results:

1. In distinguishing between prints from the left and right hand, novices' discriminability as indicated by their mean Area Under the Curve (AUC) will be better than chance (AUC = .5), resulting in a small effect size (*d* = 0 to .2), and experts AUC will be better than chance, resulting in a large effect size (*d* >.8).
2. When comparing novices to experts in discriminating prints by hand type, I expect experts to outperform novices, resulting in a large effect size (*d* > .8) in the difference between their AUC scores or sensitivity to left versus right handed prints.
3. In distinguishing between prints from different finger types or nominations (i.e., "little", "ring", "middle", "index", "thumb"), I expect novices' mean proportion correct scores to be better than chance (Proportion Correct = .2), resulting in a small effect size (*d* = 0 to .2), and experts' proportion correct to be better than chance, resulting in a large effect size (*d* = > .5).
4. When comparing novices to experts in classifying prints by finger type, I expect experts to outperform novices, resulting in a large effect size (*d* > .5) in the difference between their proportion correct scores.

Method

A view-only link to the pre-registration of this project on the Open Science Framework (OSF) is available here: https://osf.io/mdtby/?view_only=a509ad0c202d4bf4b12c6dd5e1ff1f9a. This pregresitration includes a detaled description of the methods, material, design, source code, hypotheses, predictions, planned anlyses, simulations and complete data analysis script.

2.1. Ethics

The present study was approved by the University of Adelaide School of Psychology Human Research Ethics Subcommittee (see Appendix A). Participation in this study was anonymous and participants were free to withdraw at any time. Consent was obtained from each participant before the experimental task, participants indicated their consent by signing a hard copy consent form (see Appendix B).

2.2. Particpants

2.2.1. Novices.

Novices- who had no formal training in fingerprint examination – comprised of 30 people recruited via word of mouth, poster advertisements in common areas of the University of Adelaide, and student led social media sites. Thirty novice participants (15 females, 15 males, means age 30.5, *SD* = 11.98) completed the experiment. This project was scheduled to be recruiting over the summer break so to help with recruiting novice participants, their participation put them in the draw for one of three 50-dollar gift cards, with the exception of student participating for course credit.

2.2.2. Experts.

Thirty certified fingerprint examiners (20 females, 10 males, mean age 42.63, *SD* = 8.71) were recruited from Australian policing agencies, including: South Australia Police, Victoria

Police, New South Wales Police, and the Australian Federal Police. Our goal was to reach 30 expert participants with a view to collecting data from as many experienced examiners as possible. Participation was on a volunteer basis and was subject to examiners' availability around operational requirements. Fingerprint examiners were qualified experts whose experience ranged from five years (the minimum for certifcation) to 40 years, with an average of 13.9 (SD = 8.61) years expereince.

2.2.3. Sensitivity Analysis.

As this is a first test of human fingerprint classification performance there are no established effect size estimates in the literature. Two-hundred observations from 30 participants per group yields sufficient sensitivity (power = .838) to detect small differences. On the basis of previous expert-novice studies within the domain of fingerprints, I anticipate a large difference between professional fingerprint examiners and novices (i.e., $d > .80$).

2.3. Piloting and Simulation Work

I piloted the task on three people in the lab to see if it could be completed within a thirty-minute time-frame. The original task contained 240 trials, reduced to 200 based on the pilot testing, and the sensitivity analysis reported above. To pilot our experiment and analysis script, I also ran simulated expert and novice participants through the experiment, these simulated participants were programmed to provide a random response on each trial in the experiment (i.e., a random choice of fingers 1 – 10 at a random response time between 0 and 10,00 milliseconds). I used the .txt files produced by these simulations to generate and test a LiveCode data extraction tool, and an R Markdown analysis script for plotting and analysing the data. The simulated data provide a useful model of the null hypothesis for our first analysis probing if novices and exeprts can reliably classify fingerprints by hand-type and finger-type above chance. These simulated participants are aslo helpful for debugging our experiemntal code and analysis script. If the simualted particpants' performance does not reflect that which is to be expected by chance (e.g., Area Under the Curve (AUC) = 0.5 for hand-type, proportion correct = 0.2 for finger-type in this case), then Iknow that something has gone awry. The simulated data, LiveCode data extraction tool, R Markdown source files, resutling plots, and analysis script can be downloaded at the view-only OSF link provided above. No unexpected patterns of responses were present in these simulations, indicating that the experiment is working as is should. A few plots from these simulated data in the current project are appended (see Appendix C - E).

2. 4. Design

This experiment employs a 2 (Expertise: expert, novice; between subjects) x 5 (finger-type: little, ring, middle, index, thumb; within subjects) mixed design, 'yoked' to expertise. I pre-generated sixty-four unique participant sequences. Each sequence contains 200 trials, 20 for displaying prints of each of the 10 finger-types (e.g., left and right little, ring, middle, index and thumb) in a different random order. For each of the 64 participant sequences one of the 10 prints form 200 individuals were randomly sampled, our aim in doing this was to have each sequence sampling a different set of prints but with equal numbers of each finger-type. Experts and novices were presented with the same set of sequences, so that the two groups were perfectly matched on the fingerprints they saw in the experiment, and the order in which they saw them. The first novice and expert saw sequence one, and the second novice and expert saw sequence two, and so on.

In natural settings fingerprint examiners are able to nominate multiple categories of fingers when searching for potential donors on an AFIS. However, here participants are forced to choose one of the ten finger-types, with the aim of establishing whether there is information available in fingerprints for humans to classify fingerprints by their hand-type and or finger-type, and if so whether expertise with fingerprints offers any advantage. Forcing participants to choose one of the two hand-type also allows measurement of peoples' sensitivity to information to diagnostic of "let" versus "right" (Green & Swets, 1966; Phillips, Saks, & Peterson, 2001). Moreover, this forced-choice design allows analysis of performance across two levels of specificity in the one task: participants ability to discriminate prints by hand-type (i.e., "left" and "right"), and their ability to classify them by finger-type (i.e., "little", "ring", "middle", "index", and "thumb").

2. 5. Materials

The fingerprints were sourced from the National Institute of Standards and Technology (NIST) Special Database rolled set. The full set contains 8871 prints collected in operational policing contexts, preserving natural variation in quality. I used a subset of 2000 in this project, containing 10 prints of each finger-type from 2000 individuals. The fingerprints were cropped to 500 x 500 pixels with a 400 x 400-pixel circular feathered mask. The mask was applied manually to maximise the amount of ridge detail in the fingerprint images while removing extraneous image artefacts. This process obscured the shape and size of the prints so that they were not obvious cues of the finger-type and possibly the hand-type. I decided to use controlled, fully rolled prints in this first instance, however, latent prints, by their nature, may carry contextual clues that are perhaps more diagnostic of the kind of finger and hand-type than theft them (e.g., people use their thumbs to grasp a bottle, but not to close a car door). Cropping and applying a mask also removed any labelling (e.g., "left little", "W" for whorl, or "17" for ridge count) in the outer regions of the images, which again could be cues to the finger and or hand-type. With the same aim all other original details in the images were left intact, including natural variation in contrast, hue and luminance.

2. 6. Software

The video instructions and fingerprint classification task are presented to participants on a 13-inch MacBook Pro laptop screen, with wireless over-ear headphones. The software used to generate the trail sequences, present stimuli to participants, and record their responses was developed in LiveCode (version 9.0.2 community edition) and is open source. The data analytic script was produced in RStudio, with RMarkdown, and is available to download in HTML formal at the OSF link provided above.

2. 7. Procedure

Participants first read an information sheet about the project and signed their consent forms. They then entered their demographic information, including their age, gender, years of formal experience working with fingerprints, and a unique code designed to track the expert participants over a series of fingerprint tasks as a part of a broader project (e.g., X0004L). Before beginning the experiment, participants watched an instructional video (available for viewing here: https://youtu.be/sLTJAVGzHtI), with subtitles, detailing how to complete the finger classification task with examples of each finger-type, including a little, ring, middle, index and thumb fingerprint from a left and right hand. Once they were ready to start they were presented with 200 fingerprints one at a time in the centre of the screen with 10 response buttons below labelled form left to right: “left little”, “left ring”, “left middle”, “left index”, “left thumb”, “right thumb”, “right index”, “right middle”, “right ring”, “right little”. Participants were asked to indicate “what type of finger left this print?” The 10 categories of fingers were presented in the order as they appear on a fingerprint arrest card. The print, and the 10 response options remained on the screen until participants made their decision. When one of the 10 finger-type buttons were pressed that button was highlighted followed by a pop-up confidence rating menu, with the option to indicate a confidence rating from 1 (“not confident”) to 10 (“highly confident”). As soon as participants indicated their confidence a bank screen appeared for 500 milliseconds before progressing to the next trial. Participants were given a one-minute break after 50, 100, and 150 trials, and the following instructions were provided on the screen: “take a chance to rest your eyes for a minute. The next print will appear when the 60 second time reaches zero.” Response time in milliseconds was recorded on every trial, along with each participant’s classification decisions and confidence ratings.

Results

3.1. Data Checking

I screened the data to remove any data from participants who responded in less than 500 milliseconds, or provided the same responses (e.g., “left little”) consecutively on more than 20 per cent of trails, as per the pre-specified data exclusion rule (see preregistered research plan above on the OSF linked in section 2). Individual inspection of the response time and responses indicated that no individual had responded in a way which would require their data to be excluded.

For each participant I calculated the proportion of correct responses for hand-type and finger-type discriminations over the 200 trials. I also computed participants’ Rate Correct Scores (RCS) for hand-type and finger-type discriminations, as an integrated speed-accuracy measure that expresses the proportion of correct responses produced per second (Woltz & Was, 2006). Finally, I calculated the empirical Area Under the Curve (AUC) for each participant as a measure of their sensitivity to left versus right handed prints using their cumulative confidence ratings. Confidence and response times are identical for hand-type and finger-type classifications as these were indicated by a single 10-alterantive rating. Confidence was calculated on a scale from 1 (not at all confident) to 10 (highly confident). Novices were less confident than experts, with a mean rating of 2.9 out of 10 (*SD* = 1.45), compared with 4.56 out of 10 (*SD* = 1.5). Novices were also slower to respond compared with experts, with a mean response time of 6.66 seconds (*SD* = 3.71), compared with 5.71 (*SD* = 2.65) seconds. Novices mean RCS was lower than experts, scoring 0.12 (*SD* = 0.057) and 0.039 (SD = 0.018) compared experts’ rate of 0.16 (*SD* = 0.029) and 0.058 (*SD* = 0.015) per second for hand-type and finger-type respectively.

Before proceeding with my planned parametric analyses, I conducted Shapiro-Wilk tests indicating that the data were normally distributed for both hand-type ($W = 0.977$, $p = 0.320$) and finger-type ($W = 0.972$, $p = 0.187$). I also examined density plots, box plots, and quasi-random jittered plots of the individual data for both groups to check their distributional properties, see Figure 2-4.

3.2. Hand-type classification

Both experts and novices performed well above chance at classifying fingerprints by hand-type, with experts out performing novices on every performance indicator. Novices correctly classified 64 % (0.64, $SD = 0.1$) of the fingerprints by hand-type, compared with 85% (0.85, $SD = 0.028$) for experts. Novices mean sensitivity was .65 ($SD = 0.1$), compared with 85 ($SD = 0.04$) for experts. And novices mean Rate Correct Score, accounting for their speed as well as well as their accuracy, was .12 ($SD = 0.057$), compared with .16 ($SD = 0.029$) for experts. Receiver Operating Characteristic (ROC) curves, fitted based on the first principle component of the covariance space of the inverse normal integral of participants' cumulative confidence ratings, further revealed experts' superior sensitivity to hand-type information (see Figure 3; see Vokey (2016) for details and open source code on plotting ROC using this method). Indeed, *t*-tests of participants' AUC scores showed that novices' performance classifying fingerprints by hand-type was significantly above chance ($t(29) = 7.762$, $p = <.001$, 95% CI[0.606, 0.683]) with a large effect size ($d = 1.127$). Similarly, experts' performance was also significantly above chance ($t(29) = 48.372$, $p = <.00$, 95% CI [0.834, 0.864]) with a large effect size ($d = 2.717$).

I repeated these tests using participants' Rate Correct Scores, rather than AUC, to see if these effects held when accounting for response times. These exploratory analyses revealed the same pattern of results, (t (43.011) = -3.261, $p = 0.002$, 95% CI [-0.061, -0.014]) with a large effect size (*d* = -0.842). I plotted novices' and experts' performance as measured by AUC and rate correct scores, see Figure 2. A further *t*-test of novices' and experts' performance at classifying fingerprints by hand-type revealed that experts were significantly better than novices ($t(34.484) = -10.207$, p = <.001, 95% CI [-0.245, -0.163]), with a large effect ($d = -2.635$).

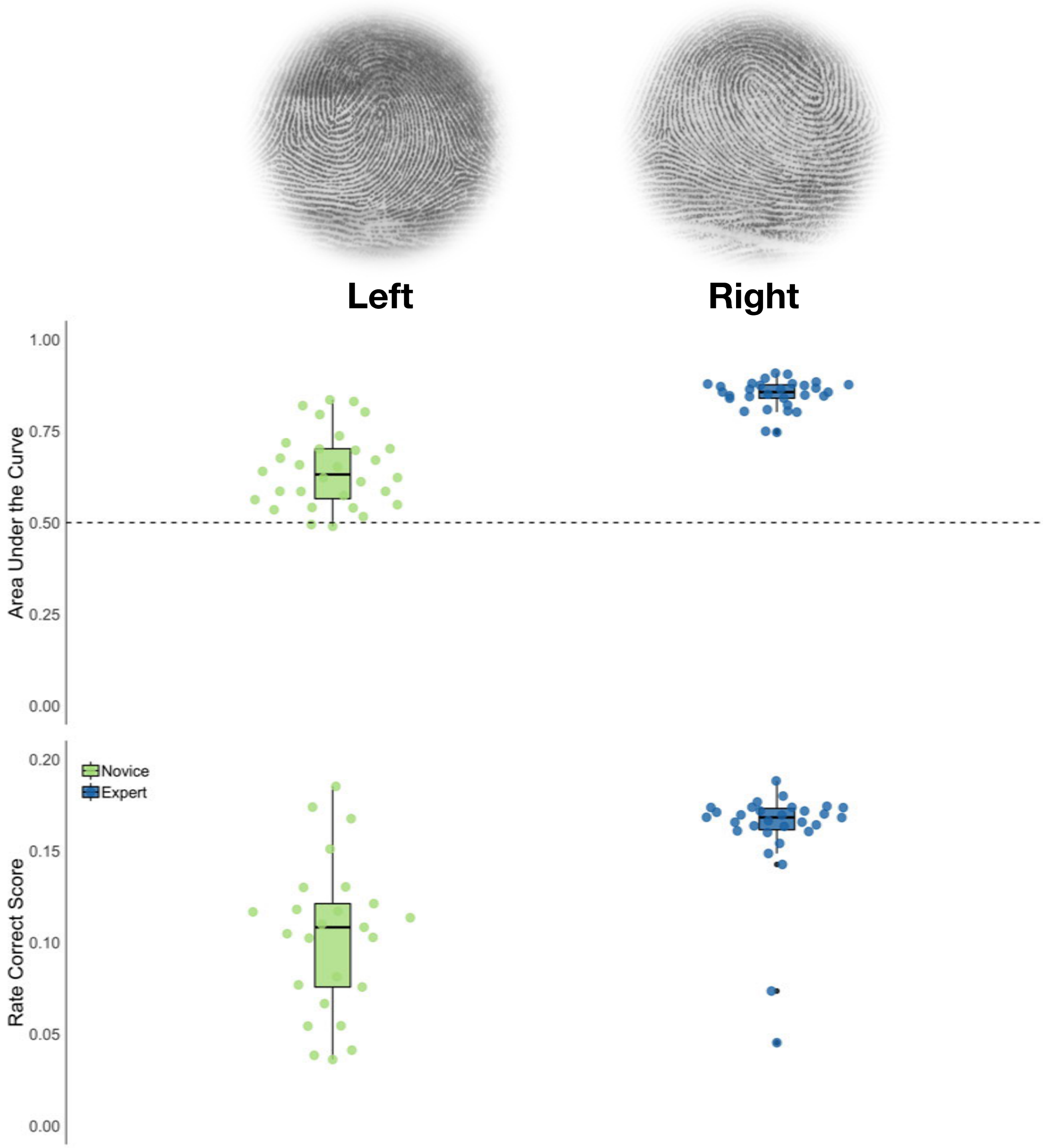

Figure 2. AUC and RCS for novices' and experts' hand-type-classifications. The images labelled "Right" and "Left" represent fingerprints from the right and left hand respectively. The dashed line in A represents the "chance level performance".

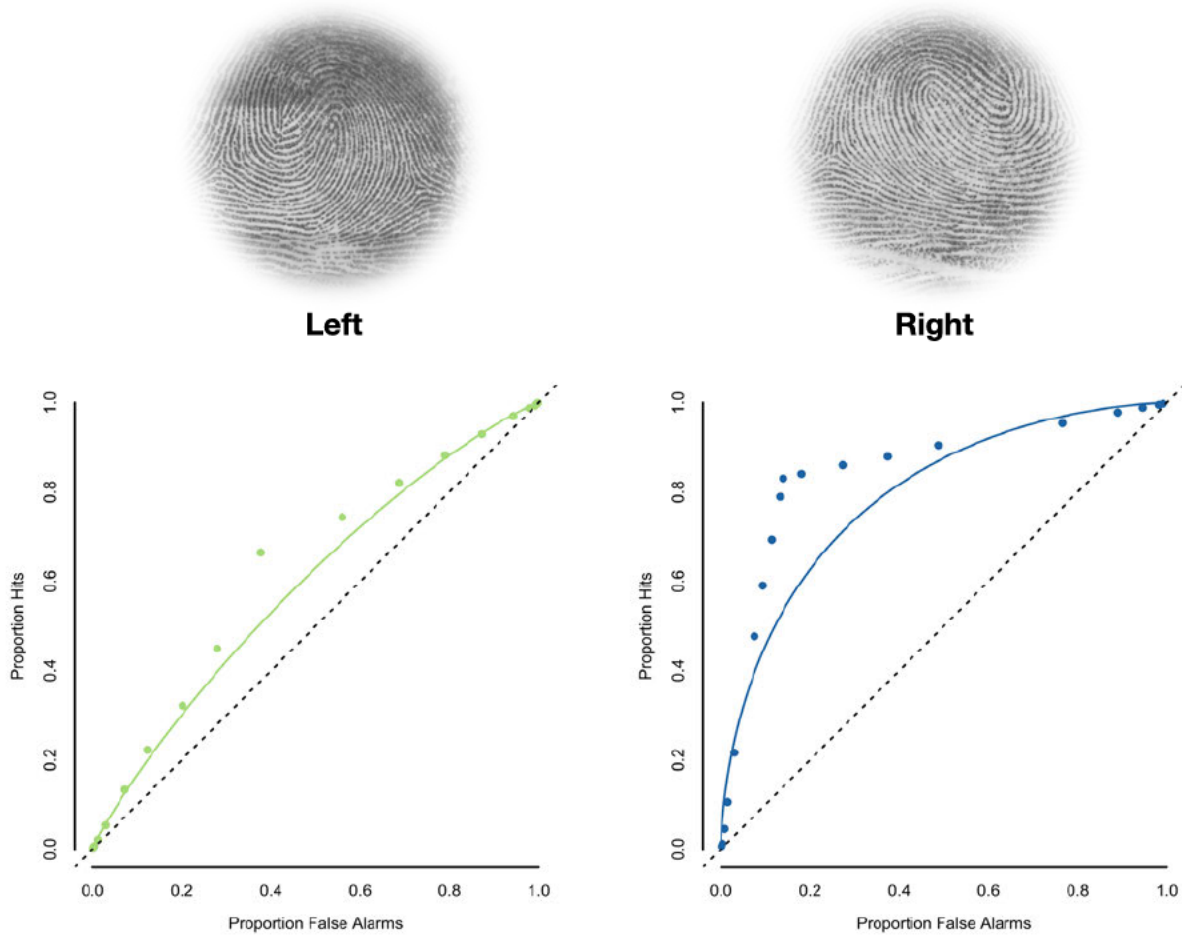

Figure 3. Empirical ROC for novices' and experts' hand-type classification. The images labelled "Right" and "Left" represent fingerprints from the right and left hand respectively. The dashed line represents the "chance level performance". The points represent the ROC calculated from the data and the solid lines represents the predictions of the model.

3.3 Finger-type classification

Novices, on average correctly classified 20% (0.2, *SD* = 0.033) of prints by finger-type, indicating chance (.2 or 1/5) responding, (*t*(29) = 0.612, *p* = 0.544, 95% CI [0.191, 0.215). Experts, on the other hand, correctly classified 31% (0.31, *SDI* =0.05) of prints by finger-type on average performing significantly above chance, (*t*(29) = 11.5, *p* = <.001, 95% CI [0.286, 0.324]) with a large effect size (*d* = 1.589). Further analyses showed that the observed difference between experts and novices in ability to classify fingerprints by finger-type was significant (*t* (-49.892) = -9.297, *p* = <.001, 95% CI [-0.123, -0.079]), with a large effect size (*d* = -2.400). An exploratory analysis using participants Rate Correct Scores, rather than Proportion Correct, as a measure of finger-type classification accuracy, revealed the same pattern of results, (*t*(56.014) = -4.580, *p* = <.001, 95% CI [-0.028, -0.011]), with a large effect (*d* = -1.182), where novices rate of correct responses per second was 0.039 (*SD* = 0.018), compared with 0.058 (*SD* = 0.15) for experts.

I conducted two further exploratory analyses examining whether people were better at classifying come finger types better than others (see Figure 2). First, I ran a mixed 2(group: Expert, Novice) x 5 (Finger Type: thumb, Index, Middle, Ring, Little) Analysis of Variance (ANOVA) on participants Proportion Correct scores, and found a significant interaction between Group and Finger -Type ($F(4, 232) = 19.303$, $p = <.001$) with a large effect size ($\eta^2_g = 0.220$). I also found a significant main effect of Group ($F(1, 58) = 86.446$, $p = <.001$) with a large effect size ($\eta^2_g = 0.813$) and Finger-Type ($F(4, 232) = 36.150$, $p = <.001$) with a large effect size (η^2_g = 0.345). I have reported generalised eta squared here as a measure of effect size to make comparisons across designs easier (Bakeman, 2005). Sum to zero contrasts, comparing performance on each of the finger-type to the others, further revealed that experts were better at classifying thumbs and index fingers, in particular, relative to the other finger-types ($F(4, 295) = 25.87$, $p = <.001$). Repeating this analysis with participants Rate Correct Score data revealed a significant interaction ($F(4, 232) = 14.380$, $p = <.001$) with a large effect ($\eta^2_g = 0.130$). There was also a main effect of Group ($F(1,58) = 20.756$, $p = <.001$) with a large effect ($\eta^2_g = 0.124$) and Finger-Type ($F(4, 232) = 32.350$, $p = <.001$) with a large effect ($\eta^2_g = 0.251$). Similarity, experts were better at classifying fingerprints as thumbs and index fingers relative to the other finger-types ($F(4, 295) = 19.23$, $p = <.001$).

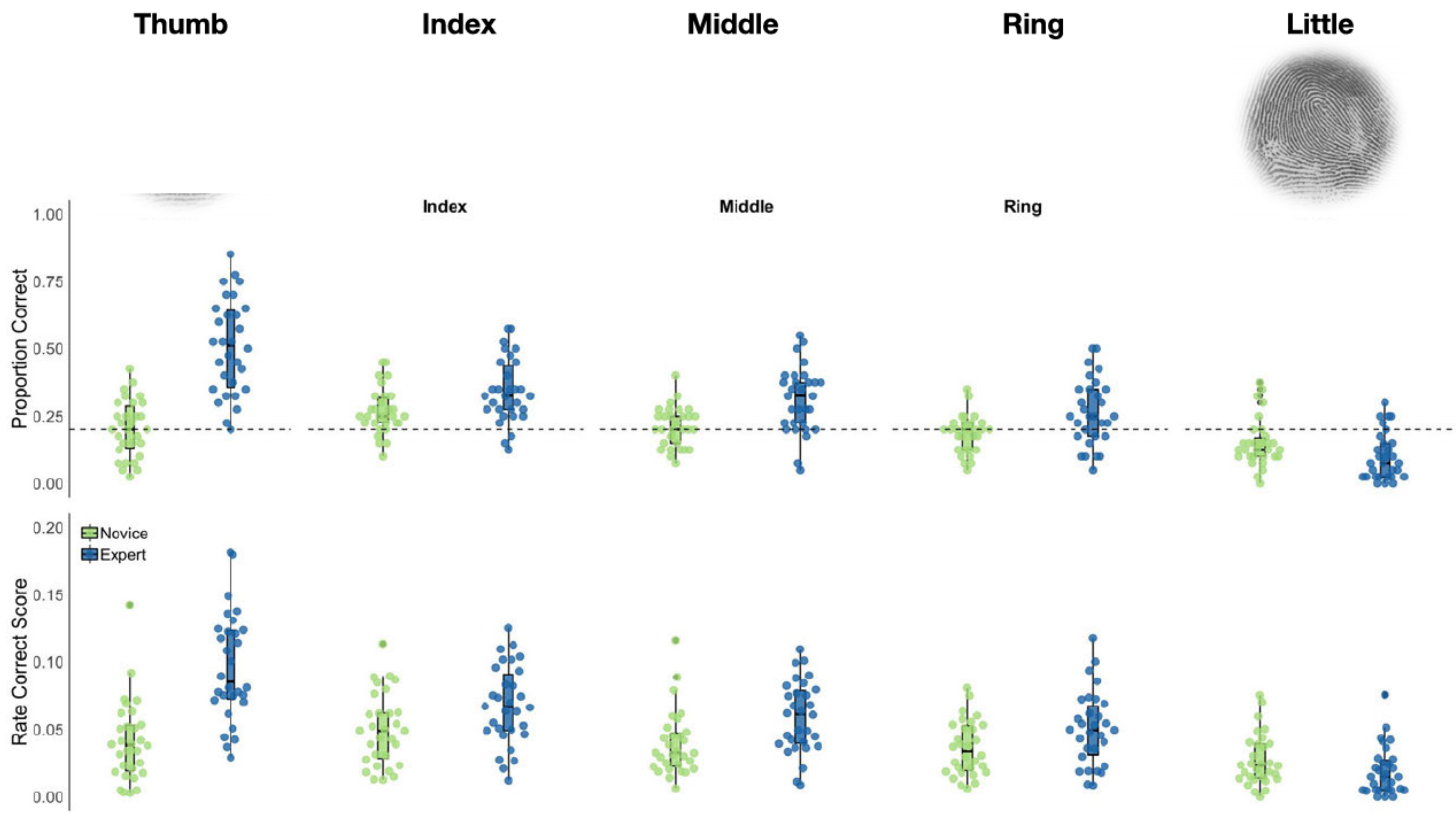

Figure 4. Proportion Correct and RCS for Experts and Novices Finger-Type Classifications. The images under each of finger-type represent a fingerprint from the corresponding finger-type.

Discussion

4.1. An Overview of the Current Study

Fingerprint examiners classify latent prints as belong to a finger-nomination – is this print from the left or right hand? and, does it come from a thumb, index, middle, ring, or little finger? – to help the algorithms of an AFIS produce a more precise list of potential candidates. However, while there is an extensive body of research which has found fingerprint examiners to display hallmarks of expertise in their ability to discriminate matching prints (Tangen, Thompson, & McCarthy, 2011; Thompson & Tangen, 2014; Searston & Tangen, 2017a), little is known about what their perceptual expertise affords them in this aspect of fingerprint examination. As such the motivation of the present study was to deliver a first test of finger-nomination classification examining novices, with no formal training with fingerprints, and experienced professional fingerprint examiners in their ability to classify a controlled set of fingerprints, for which the ground truth was known. This was achieved using a 10-alternative forced-choice task testing performance at two levels: a coarse-grained level accounting for hand-type classification (i.e., left versus right), and a fine-grained level accounting for finger-type classifications (i.e., thumb, index, middle, ring, little). The overall aim was to determine if there is visual information in fingerprints diagnostic the of hand-type and finger-type of a fingerprints' source finger, and if so, whether this is an ability that discriminates between fingerprint experts and novices.

4.2. An Overview of the Findings and the Implications

I first investigated whether there was visual information in available in fingerprints indicative of hand-type. It was anticipated that if there was visual information available that both novices' and experts' performance at classifying fingerprints by hand-type would better than chance (50%). Furthermore, that experts' performance, with their acquired repertoire of fingerprint knowledge, would be superior to that of novices. As predicted experts out-performed novices on all measures of accuracy for this task. However, both novices and experts performed exceptionally well. Novices, in fact, far exceeded my modest predictions of their performance and on average correctly classified 64% of fingerprints by hand-type, compared to 85% by experts. The data revealed that measures of novices' and experts' raw sensitivity (AUC), and rate of correct responses per second, closely mirrored their raw accuracy, for inspection see Figure 2. With both experts and novices able to perform above chance the data indicate that there is information in fingerprints diagnostic of hand-type. Furthermore, experts' superior performance suggests their expertise is offering an advantage. The present finding informs research concerned with understanding the limits of generalisation of fingerprint expertise, providing evidence suggestive that experts are able to transfer their knowledge, usually applied to very fine-grained levels of specificity (Searston & Tangen, 2017a; Searston & Tangen, 2017c), to the coarse-grained level of discriminating hand-type. This finding is corroborated by previous research which has found a general human ability, which is increased by expertise, to observe visual structure in fingerprints to make discriminations of their source (Vokey, Tangen, & Cole, 2009; Thompson, Tangen, & McCathy, 2014; Thompson, Tangen, & McCathy, 2013).

Inspection of novices' and experts' performance at hand-type classifications also indicates more within group consistency for experts, see Figure 2, with their performance displaying less overall spread than that of novices. This observation is supported by previous research which has found that experts tend to show a common threshold for determining the sufficiency, or value, of the information available in fingerprints (Ulery B. , Hicklin, Roberts, & Buscaglia, 2014). On further examination of the individual performance of novice participants, see Figure 2, some novices' performance was revealed to be on par with that of experts. This may be accounted for by previous research by Searston and Tangen (2017b), who found individual differences in perceptual abilities with fingerprints. This finding suggests that some people may have a base level aptitude for classifying fingerprints by their hand-type.

Next, I examined whether there is visual information in fingerprints indicative of finger-type (e.g., little, middle, index, etc.), anticipating that if is there is sufficient information that both novices and experts would perform above chance (20%). Again, it was expected that experts' performance would be significantly better than that of novices. The results revealed this task to be a highly discriminating one, as novices were unable to pick up on any visual information predictive of finger-type, while experts were, and on average, correctly classified 31% of fingerprints by finger-type. This finding suggests that expertise with fingerprints may facilitates access to information diagnostic of finger-type. This may be accounted for by research which has shown that the difficulty of the discrimination, in terms of how easily noise, or non-diagnostic information, can be navigated, significantly impacts discrimination ability (Thompson & Tangen, 2014; Thompson, Tangen, & McCathy, 2014). Previous perceptual expertise research has found that the more fine-grained level of specificity, or subordinate level of abstraction, which experts usually classify object at may give them resources to draw on when encountering different classification demands, and can help allowing new subordinate levels of category representations to be acquired (Tanaka, Curran, & Sheinberg, 2005). Taken together this suggests that experts were able to use their repertoire of representations to the benefit of their performance at this task, while novice, with no bank of representations, found the noise too great to reliably navigate.

I conducted an exploratory analysis of finger-type examining whether response time had been a contributing factor in overall accuracy on hand-type and finger-type classifications. Past research has found evidence of speed-accuracy trade-off for novices, where fast responding was associated with lower levels of accuracy (Searston & Tangen, 2017a). Comparing RCS and AUC for hand-type and RCS and Proportion Correct for finger-type, did not reveal evidence of a speed-accuracy relationship. However, when considering these findings in the context of the literature it should be noted that previous studies (Searston & Tangen, 2017a; Searston & Tangen, 2017c), have found novices to respond faster than experts, this was not the case in the present study. Experts (5.71 seconds) responded considerably faster than novices (6.66 seconds). While this finding was in contrast to past research the RCS for hand-type and finger-type classifications revealed a similar pattern in response latency as AUC and Proportion Correct did, indicating that response latency and response time may be useful in shedding light on trends in sensitivity.

A second finding in contrast with previous research concerned confidence ratings. Previous research has found experts to rate their abilities modestly, and novices to be somewhat over confident (Searston & Tangen, 2017c; Tangen, Thompson, & McCarthy, 2011). However, in the present study while overall confidence was low for both experts (M = 4.56/10) and novices (M = 2.9/10), experts were considerably more confident than novices. One possible explanation for this may be because this task, while aesthetically different, was based on an operational task with which experts had experience. Previous research indicates that confidence is higher when the tasks more closely call on operational demands (Tangen, Thompson, & McCarthy, 2011), then a novel task where transfer of knowledge is required (Searston & Tangen, 2017c). A possible interaction between the task demanding transfer while also calling on a familiar aspect of their work may explain the low confidence overall confidence ratings, but higher average for experts.

Visual inspection of finger-type classifications, see Figure 4, indicated a downward trend in the ability to classify fingerprints by finger-type from thumb to little finger. As such I explored whether people were better at classifying some kinds of fingers better than others. The data revealed that experts were better at classifying thumbs and index fingers, relative to other finger-types, while novices, on average, were not significantly better at any one type of finger. Further examination of this accounting for response time revealed a similar pattern of results. Overall, this finding fits with findings by Vokey, Tagen and Cole (2009), who found that peoples' accuracy when matching prints side-by-side can be a function of finger-type. Interestingly they also found index finger and thumbs, respectively, to be the most accurately discriminated. They discount the size of the pad as being a significant reason for the differences in performance on the basis that thumbs were less well discriminated than index fingers (Vokey, Tangen, & Cole, 2009). Further research into the factors driving this trend is necessary to draw any conclusions, however.

4.3. Putting the Findings into Practice

The findings outlined in this thesis provide a pattern of data which support the existence of a human ability to detect visual information in fingerprints which can be used to inform a decision about the hand-type and finger-type of the source finger. The present research has provided evidence that suggests expertise is a facilitating factor in performance in classifying fingerprints by their finger-nomination. The superior performance of experts, particularly in their ability to detect diagnostic information for finger-type, suggests that it may be possible to develop expertise in making finger-nomination classifications. Moreover, the results of the present research indicate fingerprint experts to have an impressive ability to traverse levels of specificity and transfer their expertise to coarser levels of specificity.

The benefits of developing expertise in finger-nomination classifications could prove valuable by helping to eliminate more genuine non-matching fingerprints from an AFIS generated list before the time-consuming comparison and elimination process. While examiners do not usually have time restrictions applied to their work, expertise in finger-nomination classifications could help to free up resources for other stages of examination or other casework. Such classification abilities could also help reduce the occurrence of false negatives and false positives, although verification processes catch the majority of these instances (Ulery B. T., Hicklin, Buscaglia, & Roberts, 2012), it is advantageous to have a series of safeguards in any method, as prevention is better than cure. Furthermore, the implementation of finger-nomination training, and the development of expertise, could serve as useful supporting data for examiners identity conclusions.

4.4. Strengths and Limitations of the Current Approach

This was a controlled first test of people's ability to classify fingerprints by their finger-nomination. The choice to use fully rolled prints, of which the ground truth was known, resulted in a high degree of stimulus consistency between trails and across sequences. Furthermore, the yoked expert-novice results in the controlled condition, novices, being exposed to the stimuli as the experimental condition, experts, building to the consistency and contributing to the integrity of the findings. These controlled conditions allowed for a clear light be shone on expert novice differences.

Furthermore, employing a Signal Detection Theory framework and forced-choice design allowed the performance of novices and experts to be unambiguously compared. This methodology ensured a clear picture of novices and experts' sensitivity to structure. Moreover, the present study is in line with the current trend in research on perceptual skills with fingerprints

(Tangen, Thompson, & McCarthy, Identifying fingerprint expertise, 2011; Phillips, Saks, & Peterson, 2001; Thompson & Tangen, 2014; Thompson, Tangen, & McCathy, 2014; Searston & Tangen, 2017c; Searston & Tangen, 2017a), of using Signal Detection and or forced-choice to gain understanding of fingerprint expertise.

Strengths of the test protocol itself included the use of open source software, and publicly available stimuli (see Method for details on the software and stimuli, and the OSF link above) makes this test easy to replicate and or build on as the materials are highly accessible. Also, the ability of the application to be run on laptops makes this test highly mobile, which is particularly necessary when testing a special population, such as experts, to whom access can be limited by space and time. This type of test protocol could easily be applied to research in other domain of perceptual expertise. However, data collection can be time intensive, as participants require supervision and is typically subject to availability and volunteer participation.

The joint discrimination decision did not allow for confidence or response time to be separated for the two types of classification. This limited the conclusions that could be drawn on these measures beyond those explicitly stated in this thesis as the joint confidence does not account for the relative contributions of hand and finger confidence. A further limitation of the joint classification decision is that there may have been an accuracy trade off for hand-type versus finger-type classifications, where participants my have prioritised one type of judgement over the other, regardless of the reasoning this may have impacted all participants overall accuracy. In the following section I will discuss some possible remedies to these limitations.

4.5. Future Directions

Anecdotally the experts indicated some considerations in the interpretation of the findings. Firstly, that cropping and masking the fingerprints may have hampered their ability to detect information. While the motivation in standardising the fingerprints was to remove extraneous cues which may have indicated hand or finger-type, such as the mark up on ten-print card indicating finger-type, or pressure points from how the prints were rolled indicating hand-type. With a secondary motivation to mimic latent prints, which typically have less surface area than rolled prints (Meagher, Dvornychenko, & Garris, 2014; Langenburg, Hall, & Rosemarie, 2015).The experts indicated that in so doing other diagnostic cues were also removed, mostly for finger-type, such as the ridge counts between cores and details to other landmarks. Furthermore, that while latent prints have less surface area, the way in which a latent print is left may indicate its nomination. Also indicating that they are more likely to make a finger-nomination discrimination when the prints are part of a simultaneous touch, were two or more fingerprints deposited at once, such as marks left when grasping a coffee mug. This is because the positioning of the fingerprints and variation in pressure can be indicators. Future research taking these points into consideration could examine sensitivity to hand-type and finger-type using prints from simultaneous touches as stimuli. Another direction could be to use latent prints, which would posses the natural variation in position and pressure that examiners typically come across.

The second consideration highlighted by the experts was the possibility of an accuracy trade off in favour of one type of discrimination. Experts anecdotally expressed more confidence in their ability to discriminate fingerprints by hand-type, they said more cues for hand type had remained intact in the standardised fingerprint stimuli and felt that for discriminations where they faced a high level of uncertainty for the finger-type they prioritised the correct hand-type. To remedy this, future research could separate the classifications. This could be achieved by making half of the trails hand-type classifications and half finger-type. This would also remedy the interpretations confidence and response time ratings.

Departing from this project it would interesting to investigate a training effect to establish whether expertise in this domain would increase as other perceptual skills with fingerprints increase. It would be anticipated that this would be true on the basis of past research showing clear evidence of a learning curve (Searston & Tangen, 2017c; Thompson, Tangen, & McCathy, 2014) as well as suggestive findings of the present study. Future research could also explore the inferential process behind these decisions, as this still remains unclear, and could attempt to examine the relative role of different categorical features of fingerprints and their relation to accuracy. The same could be said for further examining the performance on individual finger-types looking at features of accuracy.

Beyond this thesis the intention is to continue to collect data from expert fingerprint examiners and novices. The expert data has been collected so that individual experts' performance can be tracked over a number of fingerprint tasks, this data could be used to examine the extent to which finger-nomination ability is diagnostic of fingerprint expertise. Such research may contribute to developing a uniform training protocol with an evidence base for fingerprint examination.

4.6. Concluding Remarks

The present study has demonstrated that there are visual perceptual skills to be had in classifying fingerprints by the hand-type and finger-type of the finger from which the prints originated. The data suggest expertise to be an ameliorating factor in making these fingerprint classifications, with experts' performance exceeding that of novices on all measures of accuracy across both levels of specificity. These findings in light of the ability of experts to detect diagnostic information in finger-type, where novices could not, indicate that it is possible to develop expertise in classifying fingerprints by hand-type and finger-type. Such an ability could prove valuable in supporting conclusion of fingerprint examiners particularly when questioned in relation to criminal proceedings. This study was the first to examine this aspect of fingerprint examiners skills with fingerprints, the findings suggest that experts are able to transfer their knowledge from discriminating fingerprints for identity to hand-type and finger-type. The analyses which lead to these findings employed a forced-choice paradigm, wherein sensitivity to diagnostic information embedded in the fingerprints could assessed across two levels of specificity in the one task: at the coarse-grained level of hand-type, and at the fine-grained level of finger-type. The paradigm used in the study is in line with the current trend for visual perceptual expertise with fingerprints, as well as visual perceptual expertise more broadly. This research informs the body of research examining perceptual abilities with fingerprints, establishing a new aspect of perceptual skills with fingerprints.

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Appendices

[A - E]

Appendix A - Ethics Aproval

THE UNIVERSITY
OF ADELAIDE
AUSTRALIA

School of Psychology
University of Adelaide
North Terrace, Adelaide SA 5005
Ph. 61 8 8313 5693
Fax 61 8 8313 3770

School of Psychology: Human Research Ethics Subcommittee
Approval Sheet

Dear RACHEL

The members of the subcommittee have considered your application:

Code Number: [redacted]

Title:
A USEFUL TOOL OR GUESSWORK: A TEST OF VISUAL EXPERTISE IN CLASSIFYING FINGERPRINTS

With [Student name, if applicable] ANNELIESE CAVALLARO

I am writing to confirm that approval has been granted for this project to proceed.
Approval is granted to 12 months from the date specified below.

Yours sincerely,

[redacted]

Deputy Convenor, Human Research Ethics Subcommittee

Name: PAUL DELFABBRO

Date: 15/11/18

[redacted]

RD: Remove any reference to the HREC. It's a subcommittee app.

Appendix B – Particpant Information and Consent Form

PARTICIPANT INFORMATION SHEET

PROJECT TITLE: A useful tool or guess-work: a test of visual expertise in classifying fingerprints by finger-type

SCHOOL OF PSYCHOLOY: HUMAN RESEARCH ETHICS SUMCOMMITTEE

APPROVAL CODE:[redacted]

PRINCIPAL INVESTIGATOR: Dr. Rachel Searston

STUDENT RESEARCHER: Anneliese Cavallaro

STUDENT'S DEGREE: Bachelor of Psychological Science Honours

Dear Participant,

What is the project about?

This project examines fingerprint classification skills. Fingerprints are a common biometric used in security settings and within the criminal justice system for tasks ranging from unlocking our mobile phones to ruling out a suspect in a crime. Technology exists that can make judgements about the identity of a fingerprint, however, in high stakes decisions, such as in criminal investigation, people make the final judgement about the identity of a fingerprint. Fingerprint nomination is one of the first steps in this process.

What is involved?

You will see a series of fingerprints on a computer screen and decide what finger nomination they are (e.g., left or right little, left or right thumb etc.). We anticipate the experiment will take between <u>20 and 30 minutes</u> to complete.

Who is conducting the research and where?

This project is being conducted by Anneliese Cavallaro. This research will form the basis for the degree of Honours in Psychological Science at the University of Adelaide under the supervision of Dr. Rachel Searston. We are looking for people over the age of 18 who have no experience with fingerprints. If you chose to participate in the research, you will need to come into one of the labs, or a booked private room at the University of Adelaide North Terrace Campus. Testing will require you to use a laptop supplied by us. We ask that if you require any aids, such as glasses or a hearing aid, that you bring them along.

Are there any risks associated with participating in this project?

There are no foreseeable risks to participants health or wellbeing before, during or after participation as a result of this study. Data will be collected in the presence of the student researcher, Anneliese Cavallaro, and where appropriate measures are in place to ensure adherence to occupational health and safety issues for the benefit of the participant. Participation in this project is completely voluntary. If you agree to participate, you can withdraw from the study at any time.

What will happen to my information?

Each participant will be assigned a random number and your data will be de-identified on collection. Your data will be stored on the Open Science Framework without any identification of you as the participant. The Open Science Framework aims to assist other researchers in reproducing the experiments and analyses to make our research open and transparent. Any data collected that is potentially re-identifiable, will be stored securely on a password protected computer with multiple secure backups. Your information will only be used as described in this participant information sheet and it will only be disclosed according to the consent provided, except as required by law.

What if I have a complaint or any concerns?

This study has been approved by the School of Psychology Human Research Ethics Subcommittee (code number 18/93). If you have questions or problems associated with the practical aspects of your participation in the project, or wish to raise a concern or complaint about the project please consult the student researcher, Anneliese Cavallaro. If you wish to speak with an independent person regarding concerns or a complaint, the University's policy on research involving human participants, or your rights as a participant, please contact the convener of the Subcommittee for Human Research in the School of Psychology, Dr. Paul Delfabbro:

Phone: +61 8 8313 4936

Email: paul.delfabbro@adelaide.edu.au

Any complaint or concern will be treated in confidence and fully investigated. You will be informed of the outcome.

If I want to participate, what do I do?

If you wish to participate please contact the student researcher, **Anneliese Cavallaro**, via email (**anneliese.cavallaro@student.adelaide.edu.au**), with whom you can make a booking and ask any further questions. Alternatively, if you are a 2019 psychology student and are participating for course credit please register through the Research Participation System.

Yours sincerely,
Miss Anneliese Cavallaro and Dr. Rachel Searston

CONTACT DETAILS

Miss Anneliese Cavallaro
University of Adelaide
[redacted]

Dr. Rachel Searston
University of Adelaide, School of Psychology
[redacted]

Participant Consent Form

A useful tool or guess-work: a test of visual expertise in classifying fingerprints by finger-type

1. The nature and purpose of the study described in the attached Participant Information Sheet, so far as it affects me, has been fully explained to my satisfaction.
2. Although I understand the purpose of the research project it has also been explained that involvement may not be of any benefit to me individually.
3. I have been informed that, while information gained during this project may be published, I will not be identified, and my personal results will not be divulged as explained in the Participant Information Sheet.
4. I understand that I am free to withdraw from this study at any time without any adverse consequences.
5. I am aware that I should keep a copy of this consent from, when completed and the attached information.

Participant to complete:

I, (please print name) ………………………………………………………………………………… hereby confirm that I understand the nature of the research and consent to taking part in this research.

Signature   Date: /   /

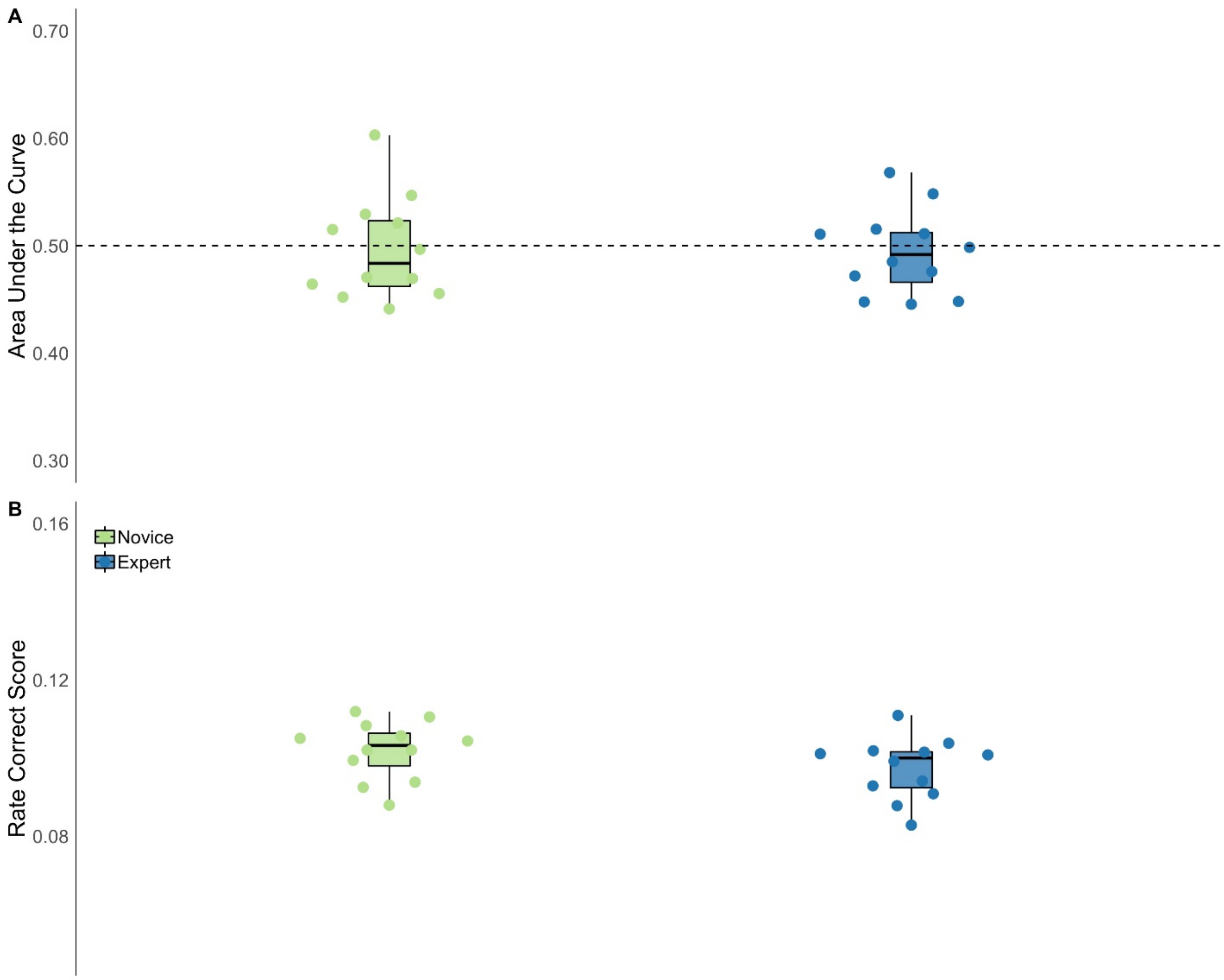
Researcher to complete:

Signature: Date: /   /

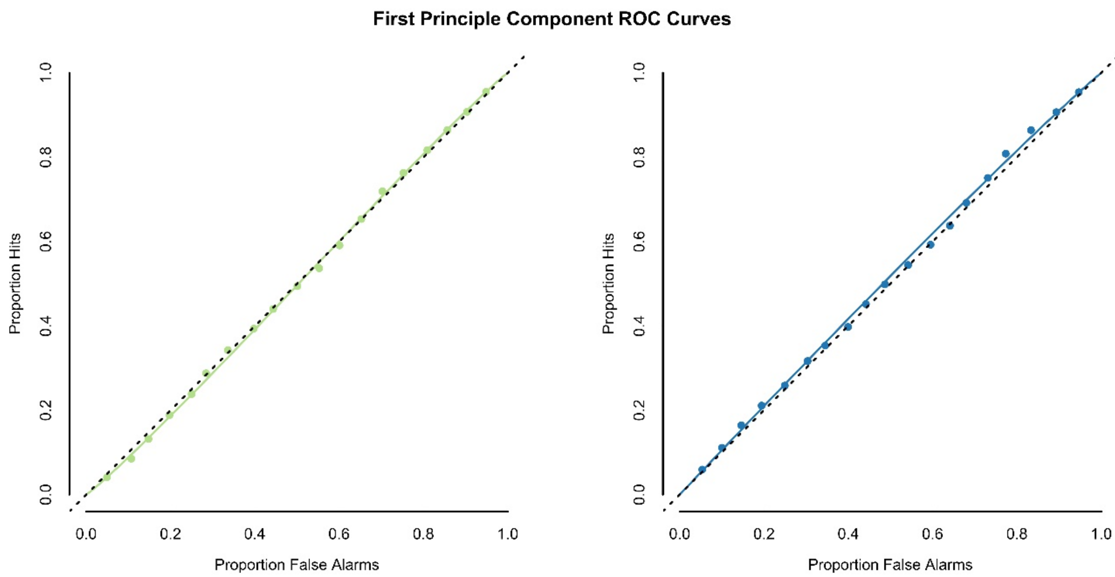
Position: ……………………………………………………………………

3

Appendix C – Simulated Hand-Type Classification Data



Appendix D – Simualted Receiver Operting Curve (ROC) for Hand-Type Data



Appendix E – Simulated Finger-Type Classification Data