Investigating age-related differences in ability to distinguish between original and manipulated images

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The materials, data, and syntax files are available online: https://osf.io/dhxvr/?view_only=2e21355038624de69d346a99f49cef8d

Abstract

Manipulated images can have serious and persistent ramifications across many domains: They have undermined trust in political campaigns, incited fear and violence, and fostered dangerous global movements. Despite growing concern about the power of manipulated images to influence people's beliefs and behavior, few studies have examined whether people can detect manipulations and the psychological processes underpinning this task. We asked 5,291 older adults, 5,291 middle-aged adults, and 5,291 young adults to detect and locate manipulations within images of real-world scenes. To determine whether a simple intervention could improve people's ability to detect manipulations, some participants viewed a short video which described the five common manipulation techniques used in the current study. Overall, participants demonstrated a limited ability to distinguish between original and manipulated images. Older adults were less accurate in detecting and locating manipulations than younger and middle-aged adults, and the effect of age varied by manipulation type. The video intervention improved performance marginally. Participants were often over-confident in their decisions, despite having limited ability to detect manipulations. Older adults were more likely than younger and middle-aged adults to report checking for shadow/lighting inconsistencies, a strategy that was not associated with improved discriminability, and less likely to report using other strategies (e.g., photometric inconsistencies) that were associated with improved discriminability. Differences in strategy use might help to account for the age differences in accuracy. Further research is needed to advance our understanding of the psychological mechanisms underlying image manipulation detection and the myriad factors that may enhance or impair performance.

Keywords: image manipulation, fake photos, visual processing, human perception, aging

Public Significance Statement

This study suggests that people have a limited ability to discriminate genuine from manipulated images of real-world scenes, and older adults' ability is slightly poorer than younger and middle-aged adults. When people are warned — via a short video intervention — about common types of image manipulations, performance improves marginally. Further research is required to account for age-related differences and to develop ways to improve people's ability to determine image authenticity.

Rapid advances in digital image technology across the 21st century have made it easy to capture, manipulate, and disseminate photos: 1.12 trillion photos were captured globally in 2020 alone, and this figure is expected to rise by 25% in 2021 (Lee, 2021). It is difficult to determine how prevalent undetected instances of fake imagery are, but the growing popularity of image-editing software, such as Snapseed, PicsArt or FaceTune, suggests that digital image manipulation has become routine practice. Moreover, numerous incidents expose how manipulated imagery can have serious and persistent ramifications at individual, organizational and societal levels. The spread of manipulated images on social media, for instance, has undermined people's trust in US political campaigns (Rafferty, 2018), incited fear and violence in Myanmar (Mozur, 2018), and contributed to the global anti-vaccination movement (Scheufele & Krause, 2019). Yet surprisingly few studies have examined how people distinguish between manipulated and authentic images. In this study, using a lifespan sample, we examine adults' ability to tell real from fake images as well as the strategies people typically adopt to detect manipulated imagery.

We know that real and fake digital images contain different characteristics or "tell-tale" signs that observers might use to determine whether those images are authentic or not. Editing a 2-D image of a 3-D scene is difficult, and forgers will often, inadvertently, leave behind irregularities or physical cues within the image. For instance, common irregularities include shadows or reflections that do not align correctly with other aspects of the scene, blurry low-resolution areas caused by splicing/copying and pasting parts from other images, or distortions at the boundaries between manipulated and non-manipulated regions (Bappy et al., 2017; Nightingale et al., 2019; Robertson et al., 2018). Such irregularities could provide vital clues that enable the observer to determine the authenticity of the image. The current study focuses on people's ability to detect such irregularities in unfamiliar images of everyday scenes.

Researchers in allied disciplines have started to investigate how people assess the credibility of online images (Kasra et al., 2018; Shen et al., 2018), but to our knowledge only one published study has tested people's ability to detect whether everyday images have been manipulated (Nightingale et al., 2017). In two experiments, 1366 adults (*M* = 26 years) viewed a series of images, half of which were authentic and half of which were manipulated (e.g., an airbrushed face or altered shadow). Overall, the results showed that people were only slightly better than chance at categorizing images as real or fake, correctly classifying a mean 66% (Expt 1) and 62% (Expt 2) of photos. Performance varied widely across the different manipulation types, from 40% correct on airbrushed photos to 80% correct on photos with objects added or removed (Expt 2), and when people did correctly identify an image as being manipulated, they were frequently unable to locate what had been manipulated. Somewhat surprisingly, there was no strong evidence that individual factors—such as the frequency with which people edit their own photos—were associated with an ability to better detect when an image had been tampered with. Taken together, the findings suggest that people have an extremely limited ability to detect if images have been manipulated.

Nightingale et al.'s (2017) study provided insufficient data to reliably examine the effect of age (only 17 people reported being 50 years or older). Therefore, the first aim of the current study was to determine the association between age and people's ability to distinguish real from fake images. Research and theory examining the effect of healthy aging suggests that declines in at least four aspects of visual processing—visual acuity, contrast sensitivity, visual-spatial attention, and perceptual processing speed—could be crucial (Erel & Levy, 2016; Spear, 1993). Although we did not set out to directly test the influence of age-related declines in these four specific areas, we briefly outline below theoretical reasons why each might result in the reduced ability to distinguish real from manipulated images.

First, age-related acuity loss (the sharpness of an image on the retina, Spear, 1993) can result in a less detailed and somewhat blurry percept of the world, and a lack of perceptual detail could make it generally more difficult for older adults to notice inconsistencies in images. Second, contrast sensitivity declines with age (Elliott et al., 1990) so when observing low-contrast regions of an image, older adults often find it more difficult than young adults to distinguish objects from the background, or to notice the separate components of an object. Third, the ability to voluntarily shift attention across the visual field declines with age (Greenwood & Parasuraman, 2004; Trick & Enns, 1998), as illustrated by some visual search tasks, particularly those in which the target is defined by a conjunction of features such as color and shape (e.g., a green circle target amongst red circles and green triangles; Humphrey & Kramer, 1997; Plude & Doussard-Roosevelt, 1989). Therefore, there might be age differences in the ability to search and then use relevant information to determine whether an image of a real-world scene has been manipulated. Finally, older adults typically experience a general slowing of perceptual processing speed which could account for age-related declines in some visual tasks (Costello et al., 2010; Salthouse, 1996).

The second aim of the current work was to determine what types of strategies people report using to determine if an image had been manipulated and whether this differed by age group. This is valuable because the focus of previous work was to examine the extent to which people can do the task rather than *how* they might do it. In the current study we wanted to learn more about how people go about distinguishing between real and manipulated images of everyday scenes.

Understanding people's ability to detect manipulated images, and how they do this, is theoretically and practically important. On the theoretical side, by identifying the factors that influence people's ability to detect manipulations, we can start to develop a theoretical framework to predict the conditions in which people will and will not do well at this task. We can also start to consider whether theory and research from different quarters of psychology such as visual search and attention, decision-making, or deception detection (just to name a few), might translate to real world situations in which people need to—typically without warning or instruction—determine whether an image is authentic. On the practical side, obviously it would be valuable to know which detection strategies, if any, work, and which sections of the population might be more or less prone to falling prey to fake images.

To summarize, the primary aim of the current study was to examine whether there are differences in young, middle-aged, and older adults' accuracy and RTs for the detection and localization of image manipulations. A further, more exploratory aim, was to gain some understanding of how people attempt to identify real and manipulated images by asking participants to report the strategies that they had used. Finally, we aimed to examine whether a simple video-based information intervention could improve people's ability to distinguish real from fake photos. To this end, some participants viewed a 1-min video that informed them of the five types of manipulation to look for and where such changes are commonly made in images before starting the task. We gathered data from a diverse sample of almost 16,000 people who were asked to distinguish between authentic and manipulated images. Participants were asked to locate where the manipulation, if any, appeared in the image, and to indicate what strategies they used to make their judgements.

Method

Transparency and Openness

The materials, including all survey questions and de-identified data on which the study conclusions are based are available, the link to access this information is provided in the Author Note. The study design, hypotheses, and analytic plan were not preregistered. Excel was used for initial data formatting and processing and the analyses were conducted in SPSS, version 27.

For the generalized estimating equation (GEE) analyses, manipulation type was included as a within-subject variable. Participants who did not self-report their gender were excluded from the analyses (the SPSS syntax file for the analyses is available and can be accessed via the link provided in the Author Note).

Our measures included participants' ability to detect and locate manipulations, as well as their response times and confidence ratings. We also asked participants to report their age, gender, level of education, interest in photography, and to indicate which (if any) strategies they used to help them in the detection and location tasks. The racial/ethnic characteristics of the sample were not measured.

Participants and Design

The study was conducted online and advertised to the general public in a press release reporting Nightingale et al.'s (2017) study (University of Warwick, 2017). Our aim was to recruit a large, opportunity sample with no geographical restrictions. A potential sampling concern is that no constraints were placed on our sample—such as screening out those with visual problems or controlling the screen size that participants completed the task using—and this may have influenced the pattern of results. Yet, by not restraining our sample, we captured the natural variability that occurs in everyday life when people encounter and discriminate real and fake images. Participants were not compensated for their participation but were offered accuracy-based feedback on their performance at the end of the task. After data cleaning[1], we had an available pool of 93,002 people who completed the task. Because a key aim was to examine the relationship between age and ability to detect image

[1] A total of 112,060 people participated in the online experiment. From this dataset, we excluded 12,361 participants as follows: 10,416 who experienced technical difficulties, 1,345 who had previously completed the experiment, and 600 who had missing RT data for at least one response. Given the current study aimed to examine age-related performance, we also removed a further 6,697 participants who chose not to report their age resulting in a pool of 93,002 participants.

manipulations, we created older, middle-aged and young samples.[2] To do so, we started by determining the maximum number of older adults available in our pool and then we selected the same number of people for the younger and middle-aged groups. The pool of participants contained 5,291 people aged 60-75 years so these people formed our older adults group. For the young and middle-aged adults, we sampled 5,291 who were aged 15-30 and 5,291 who were aged 31-59 years. We matched the young and middle-aged samples with the older sample on gender, interest in photography, and whether or not they were assigned to the information (video) condition. Table 1 shows demographic details of the final sample we analyzed which consisted of 15,873 people in total (5,291 people in each age group).

Table 1
Demographic and Information Intervention Allocation for the Young, Middle-aged, and Older Age Groups

	Young	Middle-aged	Older
Gender			
Man	3669	3669	3669
Woman	1552	1552	1552
Other	16	16	16
Prefer not to say	54	54	54
Age (years)			
M (SD)	25.33 (3.62)	41.28 (7.73)	65.00 (4.10)
Range	15–30	31–59	60–75
Information intervention			
Informed	2587	2588	2587
Uninformed	2704	2703	2704
Interest in photography			
Interested	2987	2988	2978
Not interested	2304	2303	2313

[2] We recruited an opportunity sample which meant that we were unable to control for participant age and the data are heavily skewed to young/middle-aged participants. Once we had identified the total number of adults aged 60 years or older, we then wanted to have equivalent sample sizes for the young and middle-aged groups to avoid artificially affecting the sample variance through having large differences in group size. Furthermore, our use of discrete age groups maps onto other aging research in which grouping is a common concept used to examine differences in visual processes across key stages of aging (e.g., Alain & Woods, 1999; Ball et al. 1988; Kosnik et al., 1988; Norton et al, 2009).

We used a 3 (age: young, middle-aged, older adults) × 2 (information condition: informed, uninformed) between-subjects design. A precision-for-planning-analysis revealed that 815 participants per group would provide a margin of error that is 0.10 of the population standard deviation with 95% assurance (i.e., 815 participants in each age group afforded a margin of error no larger than the target of 0.10 on 95% of occasions; Cumming, 2012, 2013). For our primary analyses, the minimum group size was 2,587 (when comparing by both age and information condition) and the maximum group size was 8,111 (when comparing the informed vs. uninformed conditions only). The Psychology Department Research Ethics Committee, working under the auspices of the Humanities and Social Sciences Research Ethics Committee (HSSREC) of the University of Warwick, approved this research. All participants provided informed consent.

Stimuli

Images

We used the same 10 photos of real-world scenes and image manipulations as used by Nightingale et al. (2017, Experiment 2). Photos were initially captured in RAW format at a resolution of 3008x2000 pixels and converted to PNGs with a resolution of 1600x1064 pixels prior to any digital editing. Nightingale et al. applied five different manipulation types (airbrushing, addition or subtraction, geometrical inconsistency, shadow inconsistency, and super-additive—where all four manipulations were combined in a single image) to six of the 10 photos, therefore creating six versions of each of the five manipulations for a total of 30 manipulated photos (see Figure 1 for examples). These 30 images formed our manipulated photo set, thus the total number of photos was 40 (10 original and 30 manipulated). Participants viewed 10 images in total; five were manipulated (one of each manipulation type) and five were original images. None of the images within a single set presented to a participant were of the same scene/photo (either manipulated or not). Each photo was checked to ensure there were no spatial distortions or substantial changes to the saliency of the altered versus original region (see Nightingale et al. for further details).

Information intervention video

We created the information intervention video using a photo from Nightingale et al.'s (2017) Experiment 1 stimulus set. The video showed the original photo and the super-additive version of that photo side-by-side on the screen (see Figure 1 for an example of an original photo and each manipulation type). As a voiceover described each of the four types of manipulation (the fifth manipulation type was the super-additive version where all four manipulations were combined in a single image), a red ellipse appeared on the super-additive version of the image to guide observers' attention to the changed region. The video was 66 s in length. Recent research examining people's performance in real-world visual search tasks suggests that short training interventions can raise people's awareness of their own attentional limitations (e.g., Gunnell et al., 2019). We tested the efficacy of a simple and short intervention that could readily be used in a variety of situations across many domains (e.g., as an advertisement for consumers, as training materials for jurors, journalists and relevant professionals).

Figure 1. Samples of photos: (a) Original, (b) Airbrushing—removal of wrinkles on the forehead and neck, removal of blemish from left cheek and top of lip, and filling in receding hairline, (c) Addition or Subtraction—addition of rubbish bins, (d) Geometrical Inconsistency— half of a tree sheered at an angle so that it appears inconsistent with the other half, (e) Shadow Inconsistency— the man's shadow has been moved so that it is inconsistent with the lighting for the rest of the scene, (f) Super-Additive—combination of all previously described manipulations.

Procedure

The procedure followed that of Nightingale et al. (2017, Experiment 2) except participants were randomly allocated, with the restriction of creating even groups, to the informed or uniformed (video intervention) condition. Other than the information video, the procedure was the same for all participants.

Participants first answered a series of questions about their demographics, beliefs about the prevalence of manipulated images in the real world, interest in photography, and experiences of taking photos (see Survey Questions for exact wording). Next, those in the informed condition were told that they would see a short tutorial about the types of image manipulation that they might encounter during the task. Immediately after watching the video, participants were asked to indicate whether they experienced any technical difficulties with seeing or hearing the video. Those in the uninformed condition did not see the information intervention video and proceeded directly to the image manipulation detection task.

Before the task started, participants were shown a practice photo and instructed to adjust their browser zoom level so that the full image was visible. Participants were then presented with 10 photos in a random order with an unlimited amount of time to view and respond. Participants viewed 10 photos, five original and five manipulated (one of each manipulation type). To measure their ability to *detect* whether each photo had been manipulated participants were asked "Do you think this photograph has been digitally altered?" The three possible response options were: (a) "Yes, and I can see exactly where the digital alteration has been made"; (b) "Yes, but I cannot see specifically what has been digitally altered"; or (c) "No." Participants then indicated their confidence in their decision using a 100-point Likert-type scale from 0 (*Not at all confident*) to 100 (*Extremely confident*). For all images (both original and manipulated), regardless of participants’ response in the detection task, we immediately measured their ability to *locate* the manipulation by presenting the same photo again with a 4×3 grid overlaid. We instructed participants to “Please select the box that you believe contains the digitally altered area of the photograph (if you believe that more than one region contains digital alteration, please select the one you feel contains the majority of the change). If you don't think the image has been altered, please just make a guess about which area might have been changed." On average, manipulations spanned two regions in the grid.

Participants were then asked to indicate whether or not they had used any particular strategies to help them to determine the authenticity of the images. Those who responded "yes" then answered a follow-up open-ended question in which they were asked to provide details of the strategies that they had used. This question did not have a set word limit. Finally, participants were asked whether they had experienced any technical difficulties while completing the experiment before receiving feedback on their performance.

Results

Task engagement check

In the manipulation detection task, the mean response time per photo was 65.8 s (SD = 261.6 s) and the median was 38.0 s (interquartile range = 26.7 to 55.9 s). In the location task, the mean response time was 20.2 s (SD = 210.1 s) and the median was 13.7 s (interquartile range = 10.0 to 19.1 s). These data suggest that participants were engaged and spent a reasonable amount of time trying to determine which photos were manipulated. We also checked for evidence of selection bias and a lack of naivete in our sample, but we did not find any evidence of this (see Supplementary Materials).

Following Cumming (2012), throughout our results we provide a precise estimate of the actual size of the effects. Further analyses of the dataset, including those revealing that people's ability to detect image manipulations might be related to the amount of physical change caused by the manipulation, are available in the Supplementary Materials.

Detecting Manipulated Versus Original Images

To examine the role of age in people's ability to distinguish between real and manipulated photos we collapsed across the two "yes" response options (i.e., "Yes, and I can see exactly where the digital alteration has been made" and "Yes, but I cannot see specifically what has been digitally altered") to calculate the overall proportion of manipulated images that were correctly identified as "manipulated" (hits) and the proportion of original images that were incorrectly identified as "manipulated" (false alarms). We used signal detection analysis (Stanislaw & Todorov, 1999) to explore both discrimination (*d'*) and response bias (*c*) and report the mean differences between age and information intervention groups in Table 2 (the actual age group and information intervention group means are reported in Table 3).

Collapsed across age, the mean *d'* score was 0.56 (95% CI [0.54, 0.57]) which although above chance (zero) remains far from perfect performance. As shown in Table 2, older adults had lower discriminability than young and middle-aged participants. All three groups showed a bias towards saying that the images were manipulated, and although only very small effects, older adults showed a reliably larger bias to respond "manipulated" than their younger counterparts. For RTs, our results revealed no reliable differences across the three age groups.

Overall, those who viewed the information intervention video were better able to discriminate between real and fake images than those who did not view the video. In addition, those who viewed the information intervention video showed a larger bias to say that the images were manipulated. Viewing the information video did not have a reliable effect on RTs.

Table 2

Mean differences in discriminability (d'), and response bias (c) for manipulation detection and mean differences in % correct for manipulation location by age and information intervention.

	Manipulation Detection	Manipulation Location

	d' [CIs]	*d*	*c* [CIs]	*d*	% [CIs]	*d*
Age						
Young vs. Older	0.16 [0.13, 0.20]	0.22	0.04 [0.02, 0.07]	0.10	8.24 [7.22, 9.25]	0.41
Middle vs. Older	0.15 [0.12, 0.19]	0.20	0.03 [0.01, 0.05]	0.06	6.49 [5.47, 7.51]	0.32
Young vs. Middle	0.01 [-0.03, 0.05]	0.01	0.02 [0.00, 0.04]	0.04	1.75 [0.75, 2.74]	0.09
Information						
Yes vs. No	0.08 [0.06, 0.10]	0.11	-0.08 [-0.10, -0.07]	0.20	5.47 [4.84, 6.10]	0.27
Age × Information						
Young, Yes vs. No	0.10 [0.05, 0.16]	0.14	-0.07 [-0.10, -0.04]	0.17	6.23 [4.85, 7.62]	0.32
Middle, Yes vs. No	0.10 [0.05, 0.16]	0.13	-0.07 [-0.10, -0.04]	0.18	5.51 [4.11, 6.91]	0.28
Older Yes vs. No	0.04 [-0.02, 0.09]	0.05	-0.11 [-0.14, -0.08]	0.23	4.67 [3.20, 6.14]	0.23

Note. For each comparison, the group on the left is the reference group and the group on the right is the non-reference group. For example, in the first row, Young is the reference group and Older the non-reference group. For *d'*, a positive difference indicates an improvement for the reference vs. non-reference group. For *c*, a positive difference indicated a reduced bias to respond "manipulated", a negative difference indicates an increased bias to respond "manipulated", zero indicates no difference. Confidence intervals (CIs) are Bonferroni corrected (99% CIs for age comparisons). For *d* values, generally 0.2, 0.5, and 0.8 are considered to reflect small, medium, and large effect sizes, respectively (Cohen, 1992).

Table 3

Mean hits, false alarms (FA), discriminability (d'), and response bias (c) scores by age overall and in both the informed and uninformed conditions.

Age Group	Hits (%)	FA (%)	*d'* [95% CIs]	*c* [95% CIs]
Overall – collapsed across information conditions				
Young	68.65	47.74	0.61 [0.59, 0.63]	-0.24 [-0.25, -0.23]
Middle	69.05	48.42	0.60 [0.58, 0.62]	-0.25 [-0.27, -0.24]
Older	67.18	52.04	0.45 [0.43, 0.47]	-0.28 [-0.30, -0.27]
Uninformed Condition				
Young	66.77	47.45	0.56 [0.54, 0.59]	-0.20 [-0.22, -0.19]
Middle	67.11	48.10	0.55 [0.53, 0.58]	-0.22 [-0.24, -0.20]
Older	65.16	50.55	0.43 [0.40, 0.46]	-0.23 [-0.25, -0.21]
Informed Condition				
Young	70.63	48.04	0.67 [0.64, 0.70]	-0.28 [-0.29, -0.26]
Middle	71.06	48.75	0.66 [0.63, 0.69]	-0.29 [-0.31, -0.28]
Older	69.28	53.60	0.47 [0.44, 0.50]	-0.34 [-0.35, -0.32]

Note. We used the loglinear approach to account for extreme hit and false alarm rates (Stanislaw & Todorov, 1999).

Young and middle-aged participants who viewed the information intervention video were better able to discriminate between real and fake images than their young and middle-aged counterparts who did not view the information intervention video. The information intervention video did not reliably improve older adults' ability to sort real from fake images.

Overall, instructing people about the possible ways in which a photo can be manipulated offered a reliable but relatively small improvement in people's ability to identify original and manipulated images.

Locating Manipulations in Images

Regardless of their response on the detection task, participants were asked to indicate the location of (or a likely location for) a manipulation by selecting one of 12 regions in the photo. As in Nightingale et al. (2017), we used a relatively liberal criterion and coded a response as correct if someone selected a region that contained any of the manipulated area or a nearby area that could be used as evidence that a manipulation had taken place.[3] As shown in Table 2, collapsed across all manipulation types, age had an effect on participants' ability to locate the manipulation.

In contrast to performance in the detection task, the information intervention had similar effects on performance across all three age groups. Specifically, young and middle-aged adults located more manipulations than the older adults, and those who viewed the information intervention video located more manipulations than those who did not. One plausible reason for the informed participants locating more of the manipulations than the uninformed participants is that they spent more time on the location task. Yet, our analysis showed that, for all three age groups, there was no reliable difference in RT between the informed and uninformed groups on the task. The information intervention video did appear to have a positive effect on participants' ability to localize manipulations, although it remains unclear why, overall, older adults made fewer accurate localizations than their younger counterparts.[4]

[3] A Monte Carlo simulation showed overall chance performance on the location task was 17% (for details, see Table 3 in Nightingale et al. (2017))
[4] Further analyses of the effect of the information intervention on participants' ability to detect and locate manipulations overall and by manipulation type are included in the Supplementary Materials.

Ability to Detect and Locate Manipulations Across the Lifespan

Focusing only on the manipulated image trials, we examined how three factors—manipulation type, age, and gender—affect people's ability to detect and locate manipulations. Although previous research has shown that performance can vary across different types of manipulation (Nightingale et al., 2017, 2019), the effect of age remains unknown. In addition, previous findings have been mixed in terms of the effect of gender on detecting and locating manipulations, and the possible interaction between gender and age is unknown, therefore we also include gender in the analysis. To examine how each of these factors influenced participants' performance on the manipulated image trials, we conducted four generalized estimating equation (GEE) analyses.

For the manipulated images, recall that we asked participants to locate the manipulation regardless of whether they correctly detected it or not—asking them to both detect and locate manipulations allowed us to segment accuracy in four ways. The manipulation could be: i) accurately detected and accurately located (hereafter, *DL*), ii) accurately detected but not accurately located (*DnL*), iii) inaccurately detected but accurately located (*nDL*), or iv) inaccurately detected and inaccurately located (*nDnL*).

Therefore, we ran four GEE analyses, one for each of the accuracy segmentations: DL, DnL, nDL, and nDnL. We used a repeated measures logistic regression because each of our four dependent variables were binary with both random and fixed effects (Liang & Zeger, 1986). The results of the GEE analyses are shown in Table 4. In each of the four accuracy segments, there was a main effect of manipulation type, a main effect of age, and a manipulation type × age interaction. To examine the interaction effect, we ran post hoc Bonferroni corrected pairwise comparisons for all levels of manipulation type by all levels of age group and discuss the largest effects (all comparisons shown in Figure 2).

The most common outcome for all three age groups was to both accurately detect and locate (DL) the manipulations. Interestingly, however, the older age group made fewer accurate detections plus accurate location responses than either the young or middle-aged groups, but the older group made more accurate detection and failed location responses than the other groups. This pattern was most prevalent for the addition or subtraction manipulations where older adults made a mean 28.4% fewer accurate detection and accurate location responses than the young age group, and 20.9% fewer than middle-aged adults (young vs. older M_{diff} 99.99% CI [24.6%, 32.1%], Cohen's d = 0.61; middle-aged vs. older M_{diff} 99.99% CI [17.1%, 24.6%], Cohen's d = 0.43). Yet for the addition or subtraction manipulations, older adults made a mean 15.5% more accurate detect, inaccurate locate responses than the young age group, and 11.4% more than the middle-aged adults (young vs. older M_{diff} 99.99% CI [12.4%, 18.5%], Cohen's d = 0.40; middle-aged vs. older M_{diff} 99.99% CI [8.4%, 14.4%], Cohen's d = 0.28). This same pattern of results was also present for the geometry and super-additive manipulation types, although the size of these effects were smaller than seen for the addition or subtraction type. For the both the airbrushing and shadow manipulations, however, the proportion of DL responses was similar across all three age groups.

The results revealed a main, albeit very small, effect of gender on DL, DnL, and nDnL responses but no gender × age interaction. Therefore, in line with previous research, our results suggest that gender has a limited influence, at most, on people's performance in detecting and locating image manipulations (Nightingale et al., 2017, 2019).

Table 4

Results of the GEE binary logistic models to determine variables that predict accuracy on the detection and location of manipulations

	DL		DnL		nDL		nDnL	
	Wald χ^2	φc	Wald χ^2	φc	Wald χ^2	φc	Wald χ^2	φc

Predictor								
Manipulation type	14515.38***	0.43	3436.43***	0.21	1666.59***	0.15	4774.51***	0.25
Age	442.37***	0.08	334.66***	0.07	41.52***	0.02	64.80***	0.03
Gender	13.02***	0.01	78.14***	0.03	0.85	<0.01	18.70***	0.02
Manipulation type*Age	559.35***	0.08	196.82***	0.05	142.69***	0.04	261.72***	0.06
Gender*Age	1.89	<0.01	0.40	<0.01	0.72	<0.01	0.38	<0.01

Note. The Wald Chi Square (χ^2) estimates the effect of the predictor variable on each of the four accuracy measures—DL, DnL, nDL, and nDnL, where *** indicates the *p* value is <0.001. Cramér's V (φc) indicates the strength of the association between the predictor and dependent variables. Interpretation of Cramér's V is dependent on the degrees of freedom (df*) calculated as the minimum number of rows, and of the columns, then minus 1. For df* = 1, Cramér’s V values of 0.10, 0.30, and 0.50 are generally considered to reflect small, medium, and large effect sizes, respectively (Cohen, 1992).
The 210 participants who chose not to disclose their gender were excluded from these analyses leaving a total sample of n = 15663.
The full-factorial model and the model including either the three-way interaction or Manipulation Type × Gender did not reach convergence for all four of the accuracy types.

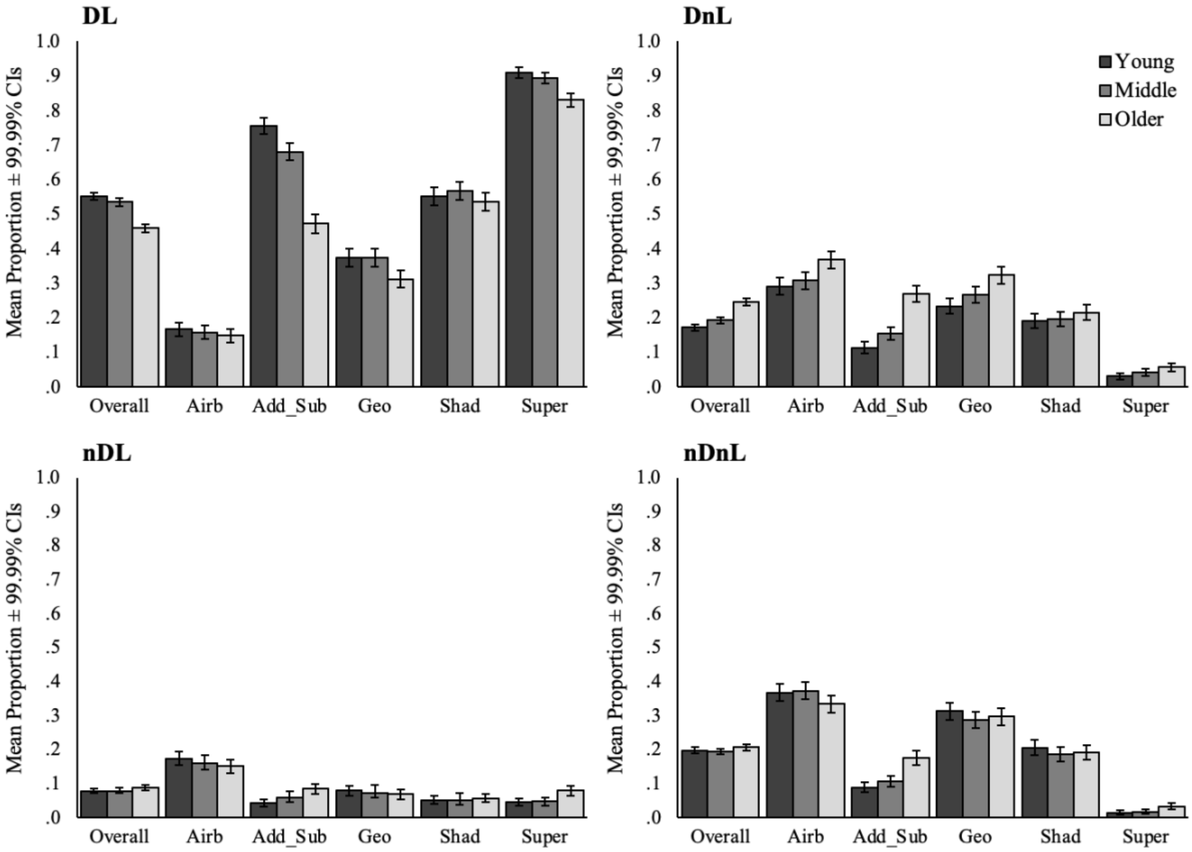

Figure 2. Mean proportion of manipulated photos accurately detected and accurately located (DL); accurately detected, inaccurately located (DnL); inaccurately detected, accurately located (nDL) and inaccurately detected, inaccurately located (nDnL) overall, and by

manipulation type and by age. Error bars represent 99.99% CIs, if the 99.99% CIs do not overlap, this provides evidence of difference that would be approximately equivalent to $p \leq 0.0001$ (Cumming & Finch, 2005).

The Relationship Between Accuracy and Confidence

An important question that remains unanswered in the empirical literature is whether people are aware of their (in)ability to detect manipulated images. We asked participants to report how confident they were in each of their judgements to determine whether their perceived confidence aligned with their observed accuracy in this task. On the one hand, if the confidence-accuracy relationship is strong—that is, people are highly confident when accurate and not very confident when inaccurate—then we have evidence that people might have some insight into their ability to distinguish between real and fake images. On the other hand, if the confidence-accuracy relationship is weak, then we should consider when and why people are prone to being over or under-confident about their decision-making, and consider ways we might address this disconnect between confidence and accuracy in real-world situations.

To examine the confidence-accuracy relationship on the detection task, we conducted confidence-accuracy-calibration (CAC) analysis (see Mickes, 2015). We produced separate CAC curves for the manipulated and original images. For each level of confidence (from 0 to 100, rounded to the nearest 10), we calculated manipulated accuracy (# correctly detected manipulated images / [# correctly detected manipulated images + # incorrectly identified manipulated images]), and original accuracy (# correctly detected original images / [# correctly detected original images + # incorrectly identified original images]). To reduce noise, we categorized the confidence ratings into five bins (0-20, 30-40, 50-60, 70-80, 90-100).

Figure 3a shows the confidence-accuracy curves for manipulated images for the young, middle-aged and older participants. Non-overlapping confidence intervals denote reliable differences between the age groups. There are three important points to note. First, the pattern of results was remarkably similar for each age group, with participants showing low accuracy levels with lower confidence ratings and relatively high accuracy levels with higher confidence ratings, yet all three groups show far from perfect calibration. Second, regardless of age, there was a tendency for participants to be over-confident, at the moderate and high levels of confidence, in their ability to accurately detect doctored images. Third, older adults correctly detected a similar proportion of manipulated images at the low and moderate (i.e., 0–60%) levels of confidence as their younger counterparts but were slightly less accurate at the highest (i.e., 90-100%) level of confidence.

Figure 3b shows the confidence-accuracy curves for the original (non-manipulated) images in the young, middle-aged and older participants. There are two key findings. First, the relationship between confidence and accuracy was extremely poor with all participants, regardless of age, showing high levels of overconfidence at every level of confidence apart from the lowest (i.e., confidence values of 0-20). Second, participants showed somewhat similar levels of accuracy at the lower levels of confidence but older adults were less accurate at the higher levels of confidence (i.e., 70-100). Overall, these findings suggest that people have limited ability to determine how confident they should feel about their image authenticity judgements.

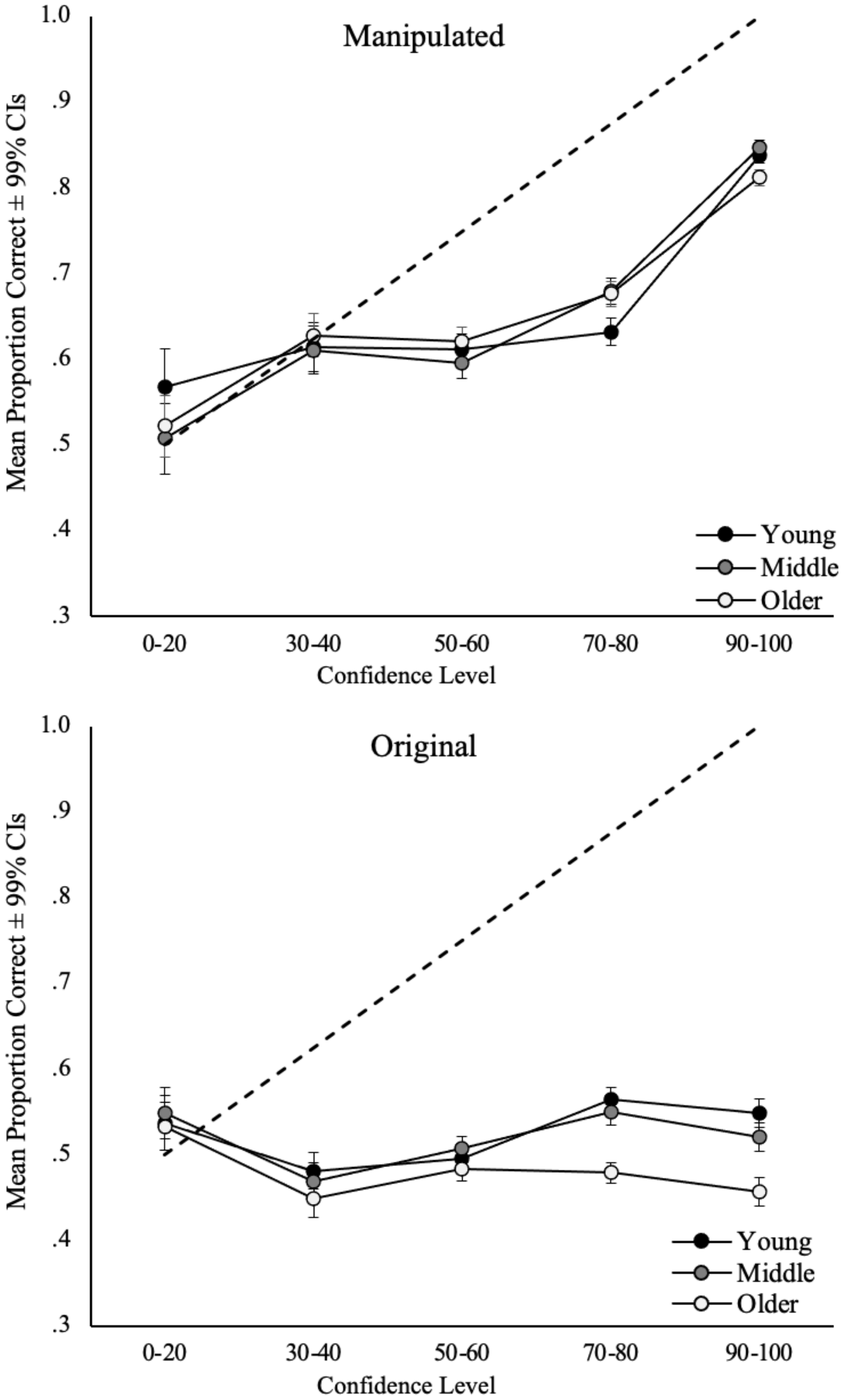

Figure 3. Confidence-accuracy curves for detection of (a) manipulated and (b) original images by young, middle-aged, and older adults. The dashed line represents perfect accuracy-confidence calibration (chance accuracy at the lowest confidence bin and perfect accuracy at the highest confidence bin). Error bars represent 99% CIs.

Strategies for Distinguishing Between Original and Manipulated Images

An exploratory aim of our study was to gain a better appreciation of how people attempt to authenticate images. What strategies do people use to determine if an image has been manipulated? Participants were asked, "When completing the task, did you use any particular strategies to help you to decide if the images had been altered or not?" Of the total 15,873 participants, 7,532 (47%) responded "yes" and provided details of the strategies they had used. We categorized these open-ended responses into 14 strategy types. Participants could report an unlimited number of strategy types, and on average, each participant provided 1.73 strategies, 95% CI [1.71, 1.75]. Four of these strategy types were determined a priori based on the strategies suggested in the information intervention video (looking for evidence of airbrushing, addition or subtraction of objects, geometrical inconsistencies, and shadow inconsistencies, see Table S1 in the Supplemental Materials for a description of each strategy type). The remaining 10 categories were developed using a data-driven approach whereby we noted key themes in participants' responses. The first author (blind to the information condition participants were allocated to) coded all 7,532 responses into these 14 categories. To assess inter-rater reliability, a second coder (also blind to condition) independently coded 20% of these responses. Cohen's κ revealed substantial to almost perfect inter-rater agreement for 10 of the categories, moderate for 2 categories, fair for 1, and slight for 1 (the "other" category) (McHugh, 2012). Table 5 shows the percentage of participants who used each of the 14 strategies.

General strategy use

For each age group, people who reported using a strategy were no more likely to accurately discriminate between original and manipulated images than people who reported using no strategies. Those who reported having used a strategy did, however, show a reliably larger bias towards saying that the images were manipulated than those who did not report using a strategy (c M_{diff} = -0.07, 95% CI [-0.09, -0.06], Cohen's d = 0.17). These results suggest that general strategy use might not be helpful in discriminating between real and fake images, and might actually lead to greater skepticism about image authenticity. Next we considered whether any of the specific strategies improved performance on the task.

Specific strategy use

The full pattern of results is shown in Table 5, in which we report the main findings and age-related differences. The most commonly reported strategy involved checking whether the direction of the shadows was consistent with the light source and older adults were more likely to report checking shadows than their young and middle-aged counterparts. Although commonly used, those reporting looking for shadow inconsistencies showed a similar ability to discriminate between real and fake images as those who did not. The second most often reported strategy was looking for photometric inconsistences (e.g., checking the color, brightness, and contrast across the different parts of the image). Older adults were less likely to report looking for photometric inconsistencies than their young and middle-aged counterparts. Unlike shadow use, those who reported looking for photometric inconsistences did show higher discriminability (without an increased bias to respond "manipulated") than those who did not report using this strategy. Older adults' greater reliance on shadows and lower reliance on photometric inconsistencies might help to account for the differences in accuracy on the task by age.

Furthermore, those who reported using two other strategies—paying careful attention and zooming in to look at parts of the image in turn and looking for evidence of cloning or repeating patterns—showed higher discriminability (without an increased bias to respond "manipulated"). Reported use of these two strategies was low across all ages.

These results suggest that it might be possible to design a training initiative to encourage greater use of the three main strategies that we found to be associated with improved discriminability without a larger bias to respond "manipulated"— (1) searching for photometric inconsistencies, (2) searching for cloning, and (3) using careful and applied attention. In addition, given the evidence on people's limited ability to determine whether or not shadows are consistent with a single light source (Farid & Bravo, 2010; Nightingale et al., 2019), it might be useful to deter people from attempting to use this strategy when trying to decide if an image is real or fake.

Table 5

Percentage of participants using each of the strategies overall, in both the uninformed and informed condition, and by age.

(%)	Overall	Information condition		Age group		
Strategies	(N = 7532)	Uninformed (N = 3983)	Informed (N = 3549)	Young (N = 2552)	Middle (N = 2380)	Older (N = 2600)
Shadow	84.47	86.19	82.53	79.08	83.91	90.27
Photometric	22.29	23.60	20.82	27.19	25.21	14.81
Geometrical	13.98	7.66	21.08	13.95	15.42	12.69
Add/sub	10.61	11.05	10.12	12.58	9.33	9.85
Changes in resolution/pixelation	9.24	10.97	7.30	11.01	10.34	6.50
Cloning/repeating patterns	5.24	5.32	5.16	3.72	7.18	4.96
General search for inconsistencies	4.74	4.22	5.33	6.70	3.70	3.77
Airbrushing	4.02	1.61	6.73	4.78	3.53	3.73
Plausibility	3.78	3.84	3.72	4.39	3.49	3.46
Extra attention/ zooming in	3.49	2.33	4.79	4.31	3.87	2.35
Overall impression/ gut feeling	1.69	1.00	2.45	1.72	1.64	1.69
Reflection	1.04	1.00	1.07	1.10	1.30	0.73
Other	4.18	1.98	6.65	3.88	3.66	4.96
Non-sensical/none	3.92	3.92	3.92	5.60	4.20	2.00

Note. Analysis included only those who indicated that they used a strategy when completing the task (*n* = 7,532).

Discussion

Across the lifespan, people demonstrated a limited ability to accurately identify manipulated images, and older adults showed slightly poorer performance on this task than younger and middle-aged adults. People's ability to detect manipulations varied across different manipulation types, and they were often over-confident in their decisions. The information video resulted in a reliable, albeit small, improvement in discriminability for the middle-aged and young adults but not for older adults. For each age group, participants who reported using strategies in general did not show greater discriminability than those who did not report using a strategy. Encouragingly, however, when looking at specific strategies, our results highlighted three that were associated with an improved ability to distinguish between original and manipulated images. Overall, the data showed that detecting manipulated images is a difficult task for all age groups, and it is particularly challenging for older adults.

Why might older adults show a poorer ability to detect manipulations than their younger counterparts? Drawing on theories of visual processing, it is possible that age-related declines in four visual mechanisms—visual acuity, contrast sensitivity, visual-spatial attention, and perceptual processing speed—could account for our results (Erel & Levy, 2016; Spear, 1993). When collapsed across manipulation type, older adults' performance in detecting and locating manipulations was poorer than their younger counterparts, and therefore each of the four mechanisms appear to offer plausible explanations for our results. When examining the pattern of results for each of the five manipulation types individually, however, there may be telling differences in older adults' performance. Notably, older adults accurately detected and located significantly fewer of the addition or subtraction, geometrical inconsistency, or super-additive manipulations than their younger counterparts, but their accuracy in detecting and locating airbrushing and shadow manipulations was similar to their younger counterparts. It seems reasonable to hypothesize that declines in older adults' visual acuity, visual spatial attention, and perceptual processing speed should lead to similar reductions in performance across the five types: given that we did not find this pattern of results, these three mechanisms cannot fully account for our findings.

Although unlikely to be the full story, it does appear that contrast sensitivity could be important, at least for detecting certain types of manipulation. In particular, the largest difference in older and younger adults' ability to detect and locate manipulations was with the addition or subtraction manipulations which in theory should be more readily detected if an individual can notice small changes in contrast. Contrast sensitivity is particularly important for noticing differences in the color and luminance of an object and its surroundings. When adding an object to a scene, for example, forgers attempt to blend the edges of the object and the background to make it look like it naturally fits in the scene. Forgers might, however, leave inconsistencies in color and luminance that make the added object stand out—the extent that this stands out to an observer will depend on their ability to see the difference in contrast (Hart et al., 2013; Scialfa et al., 2002). Research shows that aging is associated with lower visual contrast sensitivity, especially in areas of medium or high spatial frequency—such as along edges, and higher thresholds for seeing real-world stimuli such as faces, road signs, and other commonplace objects (Owsley & Sloane, 1987). Consistent with this suggestion, we found no reliable differences in detection and location performance between older and younger adults on the shadow manipulation images, where, in our stimuli at least, there tends to be high levels of contrast between the shadows and surfaces on which they cast. Of course, given that we did not directly test these visual mechanisms we can only speculate about how our findings fit with wider theory.

An alternative cognitive-based account of our results is that there are age-related differences in the awareness and/or use of the different characteristics or "tell-tale" signs that can be useful in determining image authenticity. Our analysis of the strategies that participants reported using to help them in the manipulation detection task highlighted that older adults more frequently relied on shadow-related information than their younger counterparts, and less frequently looked for photometric inconsistencies than their younger counterparts. Our results revealed that those who reported looking for photometric inconsistencies had higher discriminability in the manipulation detection task than those who did not report looking for photometric inconsistencies, yet reported shadow use did not reliably affect discriminability. Therefore, visual processing ability per se might not account for the age-related differences in our results, instead these results might be attributable to differences in people's strategy use.

Although our results do not allow us to conclusively identify which explanation best accounts for age-related differences in ability to detect manipulations, through conducting this large-scale study we have gained an initial impression of the various phenomena that might be involved. As such, our results highlight fruitful avenues for further research that seeks to tease out the precise underpinning mechanisms. Furthermore, the current findings offer some hope that research-led training initiatives could improve discriminability without increasing people's skepticism about image authenticity—therefore another important direction for future research concerns examining the effectiveness of a training initiative that gives specific and detailed information about the best clues to search for in manipulated images (rather than information about common types of manipulations, as provided in the intervention video used here). Importantly, through learning more about why people's ability to identify manipulations varies, we can begin to develop better approaches to supporting those who are most at risk of being deceived by fraudulent imagery.

Although the current study revealed three factors—age, manipulation type, and strategy—that can influence people's ability to sort real from fake images, a wide array of individual, cognitive, and environmental factors may play a role. We know, for example, that false beliefs and memories of political events are more easily created when they are congruent with a person's preexisting attitudes and ideology which suggests that the emotional and semantic context within which a photo-manipulation occurs may be important

(Frenda et al., 2013; Nightingale & Farid, 2021). Furthermore, the current study focused on people's ability to detect irregularities in images containing unfamiliar people, scenes, and objects. In the real world, people might not only attempt to determine the authenticity of unfamiliar images but of familiar ones too. As such, another interesting area for future research would be to examine people's ability to discriminate between original and manipulated images that they have some level of familiarity with.

The results of our CAC analysis suggest that not only are people poor at detecting image manipulations, but that they are also quite unaware of their limited ability—all three age groups were over-confident in their ability to accurately detect both authentic and manipulated images. At the highest level of confidence (i.e., 90-100%) older adults were significantly less likely to be accurate than younger adults. Therefore, perceived confidence is a poor indicator of accuracy when detecting image manipulations, especially for older adults. At this time, it is unclear how best to increase people's awareness of their own (in)ability to determine when an image has been manipulated, but research within the eyewitness identification literature may provide some fruitful avenues for future research. At least one study shows that instructing mock-witnesses to actively reflect on the cues they considered when identifying a perpetrator from a lineup can help to improve the confidence-accuracy relationship (Brewer et al., 2002). Perhaps similar instructions to actively reflect on the decision-making process when deciding whether an image is manipulated or not could enhance the relationship between observers' perceived confidence and the accuracy of their decisions.

It is well known that image manipulation is an ever-growing problem, and that undetected, fraudulent imagery can have serious consequences for individuals, organizations and entire societies. We now also know that people, regardless of age, have a limited ability to discriminate real from fake images and that they frequently use no strategies at all or rely on ones that are unhelpful. We have taken an initial step towards identifying the strategies that might help people to detect manipulations in images. The next step is to develop targeted training initiatives and, in time, to devise a theoretical framework that encompasses the psychological processes underpinning people's ability to sort the real from the fake.

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