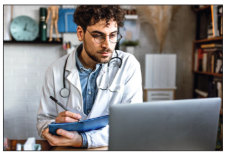
How a lack of visual fidelity in patient-generated images risks compromising care



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Internationally, contemporary primary care is reliant on digital visual information, often generated by the patient through the use of their smartphone. Primary care physicians and their teams routinely use the visual information obtained via video call or patient-uploaded images provided to make diagnoses, assess responses to treatment, and make decisions about onward referral. Yet, smartphones are not clinical instruments, and patient-generated images and video streams do not always provide a true clinical picture. Images often have poor lighting, suboptimal framing, low resolution, or software-induced alterations—including filters and artificial intelligence (AI)-based enhancements—that distort appearance and can reduce diagnostic reliability.[1–4]

Misinterpretation and distortion of such visual data can contribute to an inability to recognise clinical findings and to patient-safety incidents.[1,5] Risks are particularly critical for conditions in which colour and visual appearance are diagnostic and are exacerbated in individuals with darker skin.[6] There is little understanding of this issue among clinicians, and there are currently no minimum standards, quality-assurance processes, or guidance on when visual data are unsafe for clinical decision making.

Patient-safety concerns in video-based and image-based consultations are well documented.[7] Yet, little research has focused on the contribution of digital technology itself to such safety incidents. Digital images transmitted through consumer devices, such as an individual's smartphone, rarely represent the true visual scene. Each step in the capture–transmission–display chain introduces potential distortion, from automatic white balance and compression to display calibration. These processes are optimised for aesthetic appeal rather than diagnostic fidelity and can subtly suppress or exaggerate clinical cues such as jaundice, cyanosis, or erythema.[1–4]

Clinicians are often unaware that modern mobile telephone cameras and their software are typically developed to produce the best looking, rather than the most accurate, image. As such, smartphone cameras are not designed to give the most accurate depiction of, for example, skin colour, nor were they designed for use in clinical situations. Multiple factors can influence the accuracy of images, including the quality of the camera, the light conditions, and the ability of users to make the best use of the equipment. Colours can be distorted due to inadequate lighting, the quality of the camera, or its angle. Poor-quality screens used to view images can also introduce inaccuracies. In addition, night-time settings can change how colours are represented, removing blue light and introducing a yellow tinge. All these factors can be exacerbated through system-level technical degradations, such as low resolution, motion blur, or auto-enhancement artifacts applied by smartphone software or video platforms. Compression during poor bandwidth can introduce pixellation or blurring that hides key clinical details, such as rashes or cyanosis.[8] In video consultations and in teledermatology, such technical limitations have been recognised as obscuring important clinical cues, reducing clinical accuracy and resulting in clinical errors.[2,3]

Social media apps, such as Snapchat, now feature electronic lenses that can be used to modify photo and video content; for example, to make people appear younger, healthier, or more dynamic than in real life. The use of such electronic filters on social media[9] is increasingly common and varies by group.[10] Modern AI-based filters generate context-sensitive, highly realistic alterations, such as removing shadows or changing skin tone, and can even regenerate or erase regions of the face entirely. This generative capability makes clinical signs, such as yellowing or bruising, more likely to be unintentionally removed, creating a visually convincing but medically misleading appearance.[4]

All these factors can change the appearance of an individual to make them look less unwell; for example, a patient with anaemia might easily appear less pale, a patient with hepatitis could look less jaundiced, or a patient with sepsis might look reasonably healthy, leading to flawed decision making. More subtle signs are particularly likely to be missed, such as mild cyanosis or oedema. Most individuals are unlikely to be aware of how device characteristics, lighting conditions, or automated filters can alter visual appearance. When such distortion is unrecognised by either the patient or the clinician, visual information could be afforded unwarranted confidence, increasing the risk of misjudgement in people who are severely unwell.

Panel: Actions to mitigate risks arising from reduced visual fidelity in patient-generated images and video consultations

Patient-level actions

- Provide clear, accessible guidance (via practise websites, appointment links, or text messages) on how to submit high-quality images and videos, including using natural daylight wherever possible, avoiding mixed or artificial lighting, positioning the camera steadily and at an appropriate distance, and ensuring the relevant body part is clearly visible
- Explicitly ask patients to disable all electronic filters and beauty modes when taking photographs or joining video consultations
- Include a simple declaration (verbal or electronic) confirming that no filters are in use when images or videos are submitted
- Encourage patients to seek in-person assessment when they feel the image or video does not accurately reflect how unwell they feel
- For individuals who use video consultations frequently (eg, those in remote or rural areas), consider issuing a standardised colour reference card to be shown during consultations to help detect colour distortion

Clinician-level and service-level actions

- Train clinicians and practise teams to recognise that patient-generated images and videos are potentially distorted representations, particularly for colour-dependant signs such as jaundice, cyanosis, pallour, erythema, and rash morphology
- Build prompts into local workflows (eg, triage templates or consultation checklists) to ask about lighting conditions and filter use, to consider whether visual information is reliable enough to support decision making, and to document uncertainty related to image or video quality
- Actively confirm agreement with patients about visual impressions (eg, “Does this look like your typical skin colour?”)
- Maintain a low threshold for escalation to in-person assessment when image or video quality is suboptimal or when subtle visual signs are clinically important
- Include consideration of issues of visual fidelity in the investigation of complaints, adverse events, and patient-safety incidents involving remote consultations
- Ensure that screens used by clinicians to review clinical images are of adequate size and quality

System-level, platform-level, and regulatory actions

- Support interdisciplinary research between clinicians and computer scientists to better quantify how consumer-imaging pipelines affect the visibility of clinical signs
- Encourage video and image-exchange platforms used in health care to prompt patients to confirm that filters are disabled; alert users to poor lighting, low resolution, or excessive compression; and provide real-time feedback to improve image capture
- Explore the feasibility of a dedicated health-care mode in smartphone cameras and video platforms that minimises image enhancement and prioritises visual accuracy
- Develop minimum technical standards for platforms used in clinical care, including requirements for image-processing transparency and display quality in health-care settings
- Promote national and international guidance on the ethical use of image modification in health care, aligned with emerging regulations in related fields such as advertising and social media

There are several steps that need to be urgently taken to address such risks. First, more research is required. Interdisciplinary partnerships between computer science and clinicians, as well as access to real-world data, are needed. Accessing such data poses practical challenges, particularly around video consultations, wherein file sizes might mean many consultations are not routinely stored by health-care providers. Laboratory-based work with patients with known clinical findings, photographed and videoed using various devices, might highlight the extent to which clinical findings can be missed.

Second, the risks need to be highlighted to clinicians and the public, with mitigation approaches considered and implemented (panel). Some of these steps are relatively easy to implement, for example, asking patients to confirm the absence of filters at the start of a video consultation or when sending an image, either verbally or as part of the electronic input of personal details by the patient at the start of the consultation.

Third, technical solutions could assist. As generative AI models become more integrated into consumer devices and platforms, telehealth systems might need to incorporate content-authentication tools or metadata verification to preserve the integrity of clinical observations. Guidelines and standards for remote consultations need to evolve accordingly. Such measures are particularly important given the widespread and often invisible use of filters during remote consultations. Phones could include a health-care setting on the camera, removing filters to allow for a more realistic image to be shared.

Finally, regulation is likely to be required. Minimum standards should be mandated for screens used to view clinical images and certification should be introduced for smartphones and laptops that have clinically compatible settings. This will require international coordination and engagement with industry.

Patients' phones have become uncalibrated diagnostic tools, with still images and videos now central to remote primary care assessment. The accuracy of visual information provided cannot be assumed. Clinicians and health-care systems need to adopt pragmatic safeguards while advocating for research, policy development, and minimum requirements to ensure that visual information is reliable and safe.

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