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ORIGINAL ARTICLE

Artificial Intelligence-Based Face Transformation in Patient Seizure Videos for Privacy Protection

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Abstract

Objective: To investigate the feasibility and accuracy of artificial intelligence (AI) methods of facial deidentification in hospital-recorded epileptic seizure videos, for improved patient privacy protection while preserving clinically important features of seizure semiology.

Patients and Methods: Videos of epileptic seizures displaying seizure-related involuntary facial changes were selected from recordings at Taipei Veterans General Hospital Epilepsy Unit (between August 1, 2020 and February 28, 2023), and a single representative video frame was prepared per seizure. We tested 3 AI transformation models: (1) morphing the original facial image with a different male face; (2) substitution with a female face; and (3) cartoonization. Facial deidentification and preservation of clinically relevant facial detail were calculated based on: (1) scoring by 5 independent expert clinicians and (2) objective computation.

Results: According to the clinician scoring of 26 facial frames in 16 patients, the best compromise between deidentification and preservation of facial semiology was the cartoonization model. A male facial morphing model was superior to the cartoonization model for deidentification, but clinical detail was sacrificed. Objective similarity testing of video data reported deidentification scores in agreement with the clinicians' scores; however, preservation of semiology gave mixed results likely due to inadequate existing comparative databases.

Conclusion: Artificial intelligence-based face transformation of medical seizure videos is feasible and may be useful for patient privacy protection. In our study, the cartoonization approach provided the best compromise between deidentification and preservation of seizure semiology.

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Medical videos are important for the diagnosis and classification of many neurological disorders.[1] Paroxysmal disorders, in which symptoms and signs occur intermittently, are particularly dependent on the use of video recordings for diagnosis. Epilepsy is a common and disabling chronic neurologic condition[2] characterized by paroxysmal seizures (usually lasting seconds-minutes), which are defined as transient occurrence of signs or symptoms because of abnormal excessive or synchronous neuronal activity in the brain.[3] Seizures can be captured on video recording, most often in the hospital setting accompanied by concomitant electroencephalography (EEG) monitoring. However, increasingly, seizures are being captured on smartphones or other home video devices, which has been groundbreaking in allowing clinicians to view video data of paroxysmal events (even those that occur only rarely), filmed by the patient and their family in an ecological setting. This brings new challenges for clinical data transfer and storage including privacy protection.[4]

Review of seizure video data by expert clinicians allows detailed analysis of seizure episodes (typically showing some reproducibility for each patient), which are characterized by various patterns of abnormal movements,

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altered awareness, and sometimes behavioral or emotional changes. Analysis of seizure videos in conjunction with EEG provides a crucial information about diagnosis, epilepsy classification and brain origin of epileptic discharge, informing optimal treatment.[5] Video-EEG capture of habitual seizures is especially important in assessing the possibility of epilepsy operation, in the 1/3 of patients with focal epilepsy whose seizures do not come under control with antiseizure medications.[2,6] Expert clinicians' interpretation of seizure videos is the gold standard but is prone to observer bias and highly dependent on individual expertise and experience[5]; when rare or atypical clinical patterns are seen, outside expert opinion may be sought. Besides clinical diagnostic use, seizure videos are also a key source material for epilepsy teaching,[7] training[8] and research.[5] However, sharing seizure videos poses a problem of patient privacy especially in the context of increasing use of online medical activities. Indeed, seizure videos capture the full body including the face of patients because the facial manifestations of a seizure contribute important clinical detail. These can include emotional features,[9] color change (pallor and flushing), and various patterns of muscle contractions,[10,11] whose specific appearance and symmetry may inform likely cerebral origin of seizures.

Possible approaches to privacy protection in seizure video sharing were recently highlighted in a study investigating video-based seizure detection using machine learning, which proposed nonidentifiable vector-based representation of body movements.[12] However, not only body movements but also facial seizure manifestations (ie, involuntary seizure-induced gaze deviation, specific facial contraction patterns, or emotional facial expression) may bring key information in clinical seizure analysis.[5,13] If a method of protecting patient privacy was available that also preserved useful clinical video data, including facial information, this could facilitate safer seizure video sharing. Use of masking or blurring to obscure the face in the video might protect identity, but the inevitable reduction in quality of facial semiologic data would defeat the purpose for seizure analysis. An AI-based face-swapping approach as a means of protecting patient privacy in medical data sharing was recently tested in a clinical movement disorder research study,[14] but has not to date been investigated for epileptic seizure videos.

Here, we hypothesized that different AI-based facial transformation (source facial data) models would show different performances in terms of achieving deidentification while preserving clinical features of interest in epileptic seizure video recordings (target facial data). We studied 3 different AI models of facial transformation applied to hospital-captured seizure videos, to investigate the following: (1) the feasibility of applying facial deidentification to seizure videos; (2) the degree of facial deidentification achieved with different models; and (3) the preservation of facial seizure semiologic information.

METHODS

Material and Participants

A data set of seizure videos was compiled from the epilepsy monitoring unit, Department of Neurology, Taipei Veterans General Hospital, Neurological Institute, Taipei, Taiwan. Patients were retrospectively selected from those who had undergone elective video-EEG using standard clinical methodology for assessment of seizures between August 1, 2020 and February, 28 2023. Ethics approval was granted by the institutional review board (IRB number: 2022-07041BC) and patients provided informed consent. Videos of epileptic seizures displaying any facial changes relevant to the clinical analysis of seizure semiology (eg, facial contraction, emotional expression, and eye deviation) of satisfactory technical quality were selected. These faces of patients are the target faces.

Clinical Data Set

The final data set was composed of 26 video-recorded seizures expressing facial semiology from 16 patients (7 males and 9 females, age range at recording 9-47 years, median of 25.5 years). These patients all had drug-resistant focal epilepsy (ie, persistence of seizures despite adequate trials of at least 2 antiseizure medications,[6] and seizures arising from part of 1 cerebral hemisphere).[3] The cerebral seizure onset zone (as determined by the epilepsy team based on the results of the video-EEG and supporting data, including neuroimaging) was frontal lobe in 6 patients, temporal lobe in 7, occipital lobe in 1, frontotemporal region in 1, and temporoparietal region in 1. Five patients eventually underwent resective brain operation, 2 had radiofrequency thermocoagulation, and 4 had vagal nerve stimulation for treatment of epilepsy after presurgical evaluation.

Video Frame Preparation

The 26 video frames (1 representative facial image per seizure) presented to clinicians for analysis were chosen to include a selection of clinically relevant and clearly visible facial seizure manifestations, for example, eye gaze toward one side, grimacing, smiling, pouting, facial contraction, and lip pursing (see Supplementary Table, available online at https://www.mcpdigitalhealth.org/). Seizure data were annotated by 5 expert clinicians to allow correct selection of relevant video frames from the ictal period. A single representative frame showing the facial semiology was then prepared for each seizure. Using open-source models, video facial transformation was carried out for each selected seizure frame.

AI-Based Face Transformation Models

We tested 3 different models of facial transformation on each video frame (irrespective of patient sex), as follows: (1) morphing with a male face; (2) substitution with a female face; and (3) cartoonization, that is, converting an image or video into a cartoon style. We employed a face-swapping tool called MobileFaceSwap[15] to substitute the faces of patients with 2 desired faces. These source (artificial) faces are generated using an open-source human face generator (https://this-person-does-not-exist.com). This tool was chosen because it is an open-access, lightweight model with efficient computational time. IN addition, we used VToonify,[16] a model that specializes in transforming portrait videos into cartoon-like styles. These pre-existing tools were not specifically customized for our clinical videos in terms of fine-tuning.

Clinicians' Scoring of Deidentification and Semiology Preservation

The images (original raw video frame of the patient's face showing semiology, plus the 3 transformed video frames for that same seizure image) were shown to 5 clinicians (C-C.C., Y-C.S., S-L.F., P-T.L., H-Y.Y.), all experts in epilepsy and video-EEG. Each clinician independently reviewed and scored the frames, which were displayed on a standard hospital computer screen with one seizure (raw image + transformed images) per page, reviewed in the same order for each clinician, with no time limit for review or score. Clinicians independently scored each of the 3 transformed images according to the following: (1) degree of deidentification compared with the original image; and (2) degree of preservation of facial semiologic features. Both aspects were scored using a 3-point scale as follows: 3=good, 2=fair, and 1=poor. Results were collated and compared between observers, with a mean facial deidentification (FD) score and mean facial semiology preservation (FSP) score calculated per observer and per tested model, based on scores for that observer across all seizures. Statistical analysis of inter-observer agreement was performed using Krippendorf's α. All statistical analyses of clinicians' scores were performed using R software. The analysis of the ratings is available on Open Science Framework at https://osf.io/rxf9e/?view_only=f7c656112aba4944b029681423e4b556, and an analysis of gender congruency effect, that is, effect of gender of swapped face compared with patient face in clinicians' scores of deidentification and semiology preservation.

Computerized Scoring of Similarity and Semiology Preservation

Furthermore, we performed a computational assessment on the altered facial images to evaluate their effectiveness more objectively in terms of similarity (seen as the inverse of deidentification) and semiology preservation. To achieve this, we employed pretrained models for face recognition and facial emotion recognition. These models extract facial characteristics. These descriptors serve as features, and we calculated the cosine distance between the descriptors of the transformed and original faces. As such, lower

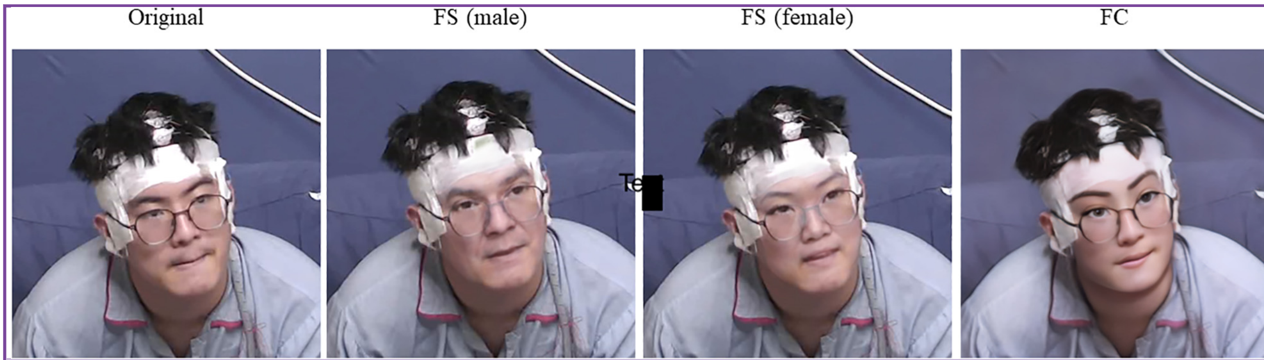

FIGURE 1. Reports of facial transformation. The Figure shows the original face, the face-swapped (FS) version to a target male or female face, and the face cartoonization.

scores of similarities indicate better deidentification.

RESULTS

Clinicians' Scores of Deidentification and Semiology Preservation

The mean scores for all video frames across all clinicians for facial deidentification were 2.48, 2.29, and 2.70, respectively for the cartoon, female, and male condition, and 2.3, 1.85, and 1.84, respectively for semiology preservation (Table 1). Overall, both the face-swapping and cartoonization techniques were scored as effective by clinicians in reducing the patient's identity. Clinicians reported a fair degree of inter-observer agreement, with an overall Krippendorf α score for FSP of 0.44 (95% confidence interval [CI], 0.33-0.55) and for FD of 0.44 (95% CI, 0.31-0.56), for 5 observers scoring 78 conditions (26 video frames $\times$ 3 models). An example of facial transformation with the 3 different models is shown in Figure 1. Figure 2 displays the average ratings assigned by the 5 clinicians regarding the transformation outcomes, focusing on the effectiveness of FD and FSP, showing overall good inter-rater agreement. The results indicate that face swapping (male) was considered most effective for deidentification but tended to reduce visibility of facial semiological features, whereas face cartoonization reported superior performance for semiologic preservation along with reasonably good FD (Figure 2). A qualitative analysis of the gender congruency effect was carried out. Violin plots found no interaction concerning the preservation score (swapping a male or a female face had similar effects) but an interaction concerning the similarity score, between the patient's gender and the gender of the source (artificial) face. This showed that swapping a female face onto a female patient's image was less well-deidentified (more similar), whereas a similar effect for male gender on deidentification scores was not seen in our study (see Supplementary Figure, available online at https://www.mcpdigitalhealth.org/). Analyses are available at https://osf.io/rxf9e/?view_only=f7c656112aba4944b029681423e4b556.

Computerized Scores of Deidentification and Semiology Preservation

The computed objective assessment of degree of facial transformation found that the face-swapping technique with a male target face consistently exhibited the best face similarity scores across different models (0.56; see Table 2).[17-21] In terms of face deidentification, a lower face similarity score is desired. This aligns with the findings from the subjective evaluation. However, when it comes to preserving facial semiology, the results are mixed across models and conditions, in contrast to the clinicians' scores, which all favored cartoonization as the best FSP scores. This discrepancy might be attributed to the differences in data sets between the pretrained models and the seizure videos.

DISCUSSION

Data sharing of identifiable medical videos for clinical, teaching and research purposes is

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largely limited by privacy concerns[5,14] (Figure 3). Methods of video facial deidentification could provide a solution for protecting patient privacy. However, standard approaches to video anonymization remove facial information, making it impossible to accurately analyze facial behavior.[14] It has been suggested that an alternative for sharing patient videos is to extract 3D key points and publish the keypoints data instead, but raw videos could provide far richer information than keypoints alone.[14] A recent study using clinical video data from patients with Parkinson disease reported quantitatively that AI-based face swapping as a deidentification approach was reliable and found invariant facial keypoints, meaning that the swapped faces retained more movement information than traditional methods of video deidentification.[14] Depending on the purpose of the video study, retained quality of facial information may be desirable, which is often the case for seizure analysis in the field of epilepsy.

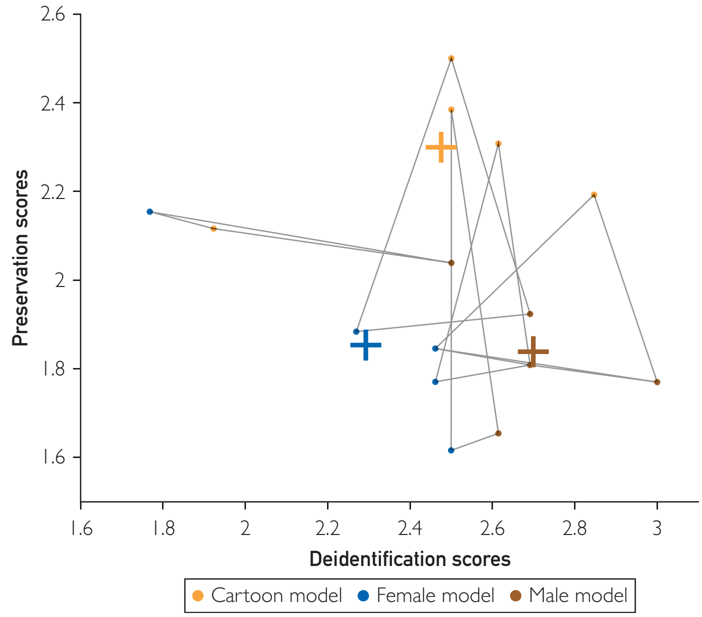

FIGURE 2. The mean facial deidentification scores (x axis) and facial semiology preservation scores (y axis) for the 5 participants and for the 3 swapped models (circle, cartoon; triangle, female; and square male). The mean scores of each participant across the 3 models are linked with a gray line. We can see that, except for 1 participant (identifiable by the lowest deidentification score), cartoon swap condition scored higher in the preservation rating than the 2 other conditions, while scoring averagely for deidentification (in between female and male conditions for all participants). For all the participants except 1, the cartoon model indicates high preservation scores, the male model indicates high deidentification scores, and the female model indicates low deidentification and low preservation scores was observed.

Clinicians' Analysis of Deidentification and Preservation of Facial Information

We have investigated for the first time the application of AI-based face-swapping models to clinical seizure videos, to assess feasibility and to evaluate differences between models. We hypothesized that differences would exist between models in terms of achieving optimal balance of deidentification and preservation of facial seizure semiology information. To this aim, we tested the following 3 transformed models in comparison with the original clinical video frame: (1) morphing the original facial image with a different male face, (2) substitution with a female face, and (3) cartoonization. According to independent scoring by 5 clinicians across 26 facial semiology frames, each viewed in the 3 different transformed conditions and compared with the original video frame, the model that best incorporated a compromise between reasonable deidentification and yet adequate preservation of facial semiology was the cartoonization model. Cartoonization first became popular in online entertainment as a means of portrait stylization of photographs and videos using AI video manipulation, but it has also been applied in other domains, for example, creating a life-like avatar to aid communication in an application for children with autism spectrum disorder.[22] Here, we used a cartoonization model[16] that produced life-like, stylized images of the patient's face, which provided satisfactory rendering of the facial semiologic signs and yet reduced facial identifiability (Figure 1).

Computerized Analysis of Deidentification and Preservation of Facial Information

We also performed objective measurement of the statistical difference between the original facial appearance and the transformed videos, using pretrained models for face recognition and facial emotion recognition and calculating the cosine distance between the descriptors of the transformed and original faces. This objective measure agreed with clinicians' subjective assessment of the model providing the best

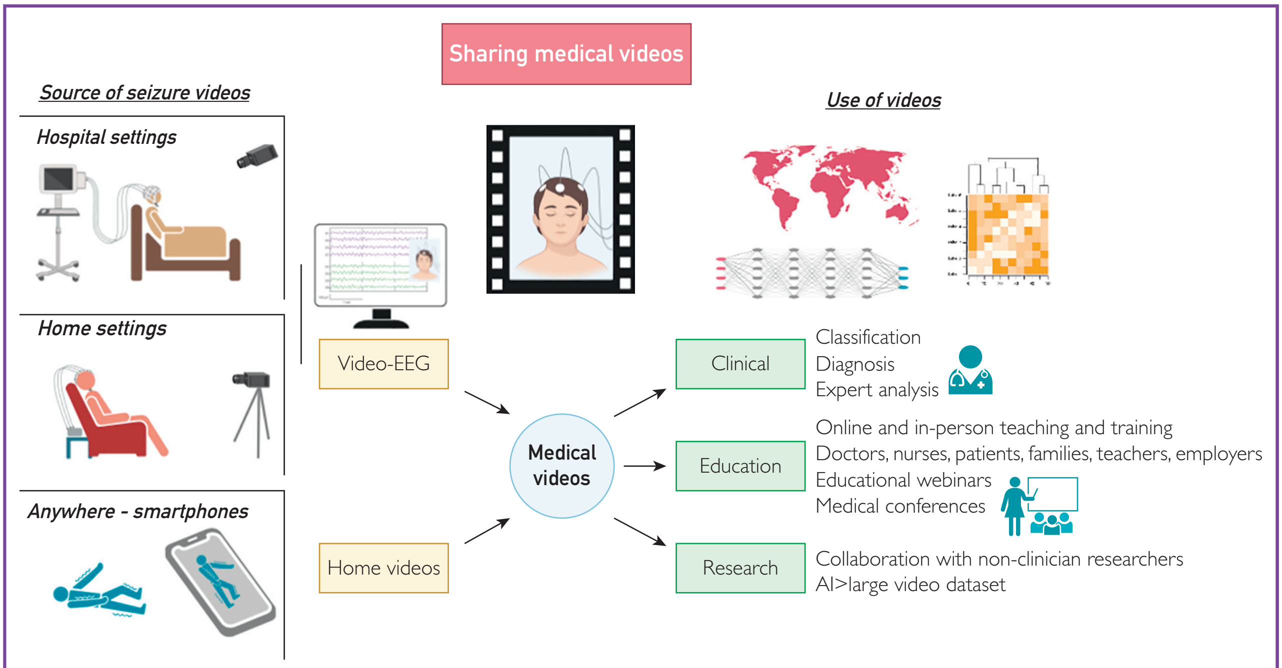

FIGURE 3. Medical video data sharing is relevant to teaching, training, and research applications in many medical disciplines. Increasing benefits but also challenges of medical video use have arisen from widespread use of smartphone videos by patients and their families, and increased use of online medical teaching and conferences. Opportunities to apply machine learning methods to medical video (eg, to classify and detect epileptic seizures) require large video data sets and collaboration with nonclinician researchers, emphasizing the need for privacy protection.

degree of deidentification (morphing with male face). In our study, objective measurement of the preservation of facial semiology reported mixed results across models, in contrast to the clinicians' scores, which all favored cartoonization for the preservation of semiologic features. This discrepancy between clinicians' and objective assessments might be attributed to the differences in data sets between the pretrained models and the seizure videos. Current facial emotion data sets for AI video and image research predominantly encompass samples representing basic emotions, such as happiness, anger, and sadness but the facial seizure semiology patterns in patients can be more intricate and implicit. The models used for comparison are emotion recognition methods, which can detect some semiological signs related to emotional states, but are not designed to detect signs related to, for example, eye movements or blinks, for which specific models exist.[23,24] Therefore, the discrepancy observed here may be because of the fact that only emotion recognition methods were used, which are not built to detect some of the heterogeneous facial semiology features in the present data set. This suggests the need for a more specialized face model dedicated to semiology analysis when incorporating AI methods for automatic analysis.

Privacy Issues in Data Sharing of Medical Videos

In epilepsy care, seizure videos constitute fundamental and widely-used source data for clinical diagnosis and also teaching,[7] training[8] and research.[5] Not only hospital-acquired video recording but also smartphone[25] and other home video methods[26] are becoming increasingly employed for seizure capture, highlighting the need for new frameworks for optimal video data transfer, secure storage, and analysis.[27] Medical videos are employed in assessment of neurological conditions more generally.[1] Particularly since the advent of

TABLE 1. Clinicians' Mean Scores of AI-Based Video Transformation Models[a]

	Clinician Raters	Cartoon	Female	Male
Deidentification				
	A	2.50	2.50	2.62
	B	2.50	2.27	2.69
	C	2.62	2.46	2.69
	D	1.92	1.77	2.50
	E	2.85	2.46	3.00
	Average score	2.48	2.29	2.70
Preservation				
	A	2.38	1.62	1.65
	B	2.50	1.88	1.92
	C	2.31	1.77	1.81
	D	2.12	2.15	2.04
	E	2.19	1.85	1.77
	Average score	2.30	1.85	1.84

[a]Each of the clinician raters scored all 26 facial video frames displaying seizure-related facial change, across 3 AI-transformed models with comparison with the raw clinical video frame: cartoonization, substitution with a female face and morphing with a male face. Clinicians independently scored each of the 3 transformed images according to the following: (1) degree of deidentification compared with the original image; and (2) degree of preservation of facial semiologic features. Both aspects were scored using a 3-point scale, as follows: 3=good, 2=fair, and 1=poor. The mean scores for each rater across all frames are shown. The most effective model for deidentification (highest score) was the male morphing model. The most effective model for preservation of facial clinical detail was the cartoonization model.

online medical conferences and internet-based teaching forums and platforms, potential widespread diffusion of medical videos may risk compromising patient privacy because the responsible clinician no longer maintains complete control of this sensitive data, which in the past was stored on physical cassettes or disks. Reliable means of deidentifying facial video data in medical videos could help mitigate privacy concerns, allowing for more effective data sharing that would be useful for research, teaching and training purposes, including internet-based teaching that allows under-served geographical regions to benefit from expert education.[7]

Data Sharing of Medical Videos in Research

Providing important value in teaching and training, seizure videos are a main data source for epilepsy research.[5] Seizure video data lends itself well to deep learning approaches,[12,13,28-30] and these show promise for automated seizure video classification with important clinical implications, for example, video-based automatic detection of high-risk tonic-clonic seizures, which could reduce seizure-related morbidity and mortality.[12,30] Optimizing deep learning methods requires large, representative data sets that must respect ethical and legal issues related to medical data access,[31] and collaboration with nonclinician researchers.[32] Epileptic seizures are characterized by a vast repertoire of often complex semiologic patterns, and data sets must be both carefully curated by expert clinicians and large enough for meaningful study.[5,6,32] A main barrier to assembling seizure video data sets of optimal scale that adequately reflect the heterogeneity of different seizure patterns relates to privacy concerns.[5,12] Privacy protection using deidentification of seizure videos might present a step towards facilitating clinical video data sharing, but ideally this should retain some facial information. For example, if seizure-related emotional change is present, this tends to be reflected in altered facial expression[9] and may imply specific seizure classification or brain localization.[3,9,13] In previous work, combined region and landmark-based automated facial detection and classification could accurately distinguish spontaneous facial expressions from involuntary facial changes occurring during temporal lobe seizures.[33] In another study, automated classification of

TABLE 2. Computerized Objective Scores of AI-Based Video Transformation Models[a]

	Model	Cartoon	Female	Male
Similarity				
	VGG[17]	0.82	0.72	0.68
	Facenet[18]	0.64	0.57	0.33
	Openface[19]	0.81	0.79	0.74
	Deepface[b]	0.85	0.83	0.83
	ArcFace[20]	0.60	0.43	0.25
	Average score	0.74	0.67	0.56
Preservation				
	FECNet[21]	0.91	0.92	0.90
	Deepface[b]	0.77	0.76	0.77
	WuJie[c]	0.70	0.78	0.78
	RMN[d]	0.95	0.95	0.95
	Average score	0.83	0.86	0.85

[a]Face and facial expression similarity between transformed faces and original ones have been calculated. The scores are the cosine similarity of the used face or expression descriptors. Lower scores of similarity indicate better deidentification.
[b]https://github.com/serengil/deepface
[c]https://github.com/WuJie1010/Facial-Expression-Recognition.Pytorch
[d]https://github.com/phamquiluan/ResidualMaskingNetwork

seizures according to presence or absence of emotional semiology found that spatiotemporal features of facial appearance reported best accuracy for emotion detection (F1 score 0.84).[13] Because loss of facial information could affect automated classification accuracy for some seizure patterns, a balance between optimal deidentification and fidelity of facial information is important when considering ways to mitigate privacy issues for epileptic seizure video data sharing.

Strengths and Weaknesses

Strengths of the study include its novelty because to our knowledge this is the first application of AI-based face swapping to epileptic seizure videos, with the goal of mitigating privacy concerns for clinical data sharing. Another strength is the fact that we have tried to quantify not only degree of deidentification afforded by 3 different models but also the degree of preservation of facial clinical information because the balance of these 2 somewhat opposing attributes is essential to clinical usefulness in our field. We have done so using a combination of both subjective clinicians' analysis (based on 5 clinicians' independent semi-quantified scores) and objective computerized analysis, applied to 26 diverse involuntary facial expressions occurring during epileptic seizures captured on clinical video, in male and female patients of both pediatric and adult age groups. Weaknesses include the fact that existing open-source AI face-swapping tools were employed, with no fine-tuning for seizure videos; on contrary, use of open-source models will allow this study to be replicated on other data sets. We did not have a well-suited AI facial expression database for objectively assessing the similarity of the face-swapped semiology preservation because such a database does not yet exist. Further work could use fine-tuning of AI models to improve their applicability to seizure facial video data. Last, our study analyzed representative video frames (ie, static images) rather than dynamic video data. Single video frames are less informative and robust than dynamic video, for analyzing certain semiologic features that are temporally variable. On contrary, single video frames can often have clinical value, eg, figures for medical teaching. We have begun with single video frames as a proof-of-concept study, to test the value of different transformative AI models for accuracy. A next step will be to analyze raw

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seizure videos, which necessarily requires more computational power.

CONCLUSION

The results suggest that AI-based face swapping in clinical videos could have a potential role in mitigating privacy concerns when seizure or video data are to be shared beyond the immediate clinical environment. This could also be of value in other medical video data sharing outside of the field of epilepsy, especially where preservation of quality of facial video information is important, for example classification of movement disorders[1] or clinical and research evaluation of emotional expression in psychiatric conditions.[34] We acknowledge; however, that it might be important to consider whether facial deidentification is enough for privacy preservation. Some patients may be identified by other signs (specific jewellery and clothes), in which case simple facial deidentification might not suffice to preserve privacy; in addition, family or staff members sometimes appear in video clips. Vocalization may be another identifiable feature. Further investigation is required to assess optimal face-swapping methods and their effectiveness in larger data sets, which might be facilitated by developing a user-friendly software application for ready transformation of clinical video material in the hospital setting, and applications that could be used to transform videos acquired on a mobile device. As all patients reported here were all of Asian facial appearance, study of other populations could be of interest to check validity of face-swapping methods across facial types. Future studies should test effects of different variables of facial morphing in more detail, for example, effects of age (young or old) and ethnic appearance (eg, Asian or Caucasian). We observed that in the models used here, eye gaze position seemed somewhat less robustly preserved than the lower part of the face (eg, mouth contraction) for some examples. This aspect would be of interest to examine in a larger sample, and to test additional models incorporating eye tracking.

Some caveats also require further consideration. Video manipulation methods can be used to control and misuse identity, and it has been highlighted that education, training, and governance around deepfake practices in digital media are urgently needed, to avoid negative societal consequences.[35] Another factor to be considered is the ethical context of altering facial features of a patient's video, which requires attention to respectful use of video data.

POTENTIAL COMPETING INTERESTS

The authors report no competing interests.

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SUPPLEMENTAL ONLINE MATERIAL

Supplemental material can be found online at https://www.mcpdigitalhealth.org/. Supplemental material attached to journal articles has not been edited, and the authors take responsibility for the accuracy of all data

Abbreviations and Acronyms: **AI,** artificial intelligence; **EEG,** electroencephalography; **3D,** three-dimensional; **FD,** facial deidentification; **FSP,** facial semiology preservation

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