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Artificial intelligence and digital solutions for myopia

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Abstract:

Myopia as an uncorrected visual impairment is recognized as a global public health issue with an increasing burden on health-care systems. Moreover, high myopia increases one's risk of developing pathologic myopia, which can lead to irreversible visual impairment. Thus, increased resources are needed for the early identification of complications, timely intervention to prevent myopia progression, and treatment of complications. Emerging artificial intelligence (AI) and digital technologies may have the potential to tackle these unmet needs through automated detection for screening and risk stratification, individualized prediction, and prognostication of myopia progression. AI applications in myopia for children and adults have been developed for the detection, diagnosis, and prediction of progression. Novel AI technologies, including multimodal AI, explainable AI, federated learning, automated machine learning, and blockchain, may further improve prediction performance, safety, accessibility, and also circumvent concerns of explainability. Digital technology advancements include digital therapeutics, self-monitoring devices, virtual reality or augmented reality technology, and wearable devices – which provide possible avenues for monitoring myopia progression and control. However, there are challenges in the implementation of these technologies, which include requirements for specific infrastructure and resources, demonstrating clinically acceptable performance and safety of data management. Nonetheless, this remains an evolving field with the potential to address the growing global burden of myopia.

Keywords:

Artificial intelligence, digital technology, myopia, telemedicine

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Introduction

Myopia is one of the major growing public health challenges. Currently, over 2 billion people worldwide have myopia (which is defined as ≥ −0.5 dioptres), 15% of whom have high myopia (defined as ≥ −5 dioptres).[1] In 2020, an estimated 161 million people globally suffered from blindness or moderate-to-severe vision loss from uncorrected refractive errors, cementing it as the leading cause of vision impairment.[2] By 2050, myopia is expected to affect almost 5 billion individuals worldwide, nearly half of the projected global population [Figure 1],[1] which will pose a huge burden on health services to diagnose, including providing optical corrections, diagnosing and treating vision-threatening complications caused by high myopia. Uncorrected myopia and myopic macular degeneration (MMD), a common complication of high myopia, were responsible for causing nearly US$250 billion loss of productivity worldwide in 2015.[3,4]

High myopia and pathologic myopia are largely responsible for myopia-related irreversible visual impairment, for example, glaucoma, retinal detachment, myopic maculopathy, and macular choroidal neovascularization (CNV).[5] Therefore, early identification of children "at-risk" of developing high myopia, followed by regular follow-up to monitor the progression of myopia to allow for early intervention, is essential to reduce the potential risk of irreversible blindness.[6] However, current health-care resources may have difficulty

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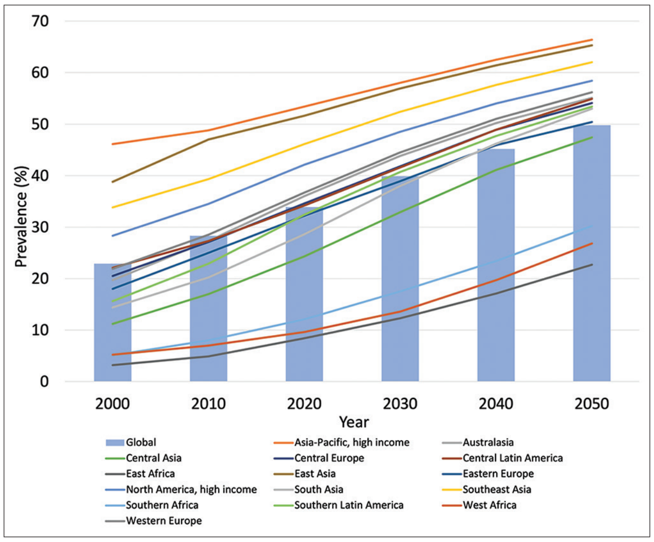

Figure 1: Prevalence of Myopia Estimated for Each Global Burden of Disease Region between 2000 and 2050[1]

coping with this growing burden.[6,7] Recently, the emergence of artificial intelligence (AI) and digital technology, such as telemedicine, has the potential to address this global health need. To date, many studies have been described applying AI and digital technology into different aspects of the clinical management of myopia, and some have achieved significant results.[8] In this review, we summarize the current applications and advances in AI and digital technology for myopia, and discuss the current challenges in implementation into clinical practice.

Clinical Unmet Needs in Myopia

For the diagnosis and detection of myopia, the current clinical practice requires visual acuity and refractive assessment, and may require comprehensive eye examinations to diagnose pathologic myopia and related complications, which may require sophisticated imaging systems and skilled workforce.[9,10] This may be circumvented using AI and digital technology by developing screening or risk stratification tools for the automated detection of myopia with its related complications.

Currently, to monitor and predict the myopia progression of patients, multiple follow-up visits are required to document patients' progression of myopia or the development of pathological changes associated with myopia, putting extra burden on existing strained medical resources. With robust AI models that can predict childhood myopia progression or the development of pathological changes in highly myopic patients, this may reduce the economic burdens caused by myopia.

Current interventions for childhood myopia control include environmental interventions such as increasing time outdoors;[11] optical interventions such as peripheral myopic defocus spectacles and orthokeratology;[12] pharmaceutical interventions such as atropine eye drops.[13-15] The management of pathologic myopia may also include surgical treatment and anti-vascular endothelial growth factor therapy.[5] AI models based on big medical data, however, have the potential for individualized treatment and assisting in achieving precision medicine in myopia.[16,17]

Artificial Intelligence in Myopia

Background of artificial intelligence

AI was conceptualized in 1956.[18] The term "machine learning" (ML) was coined in 1959, which would entail that "the computer should have the ability to learn using various statistical techniques, without being explicitly programmed."[19] Using ML, algorithms can learn and make predictions based on the data that has been fed into the training process, using either a supervised or un-supervised approach. ML has been widely adopted in applications such as predictive analytics and computer vision using complex mathematical models. With the advent of graphic processing units (GPUs), the availability of big data and low-cost sensors, and deep learning (DL) techniques, this area has sparked tremendous interest and has been applied across many industries.[20] In particular, DL has emerged recently as an AI technique facilitating the analysis of unstructured data, such as language, images, and video. In ophthalmology, DL has been most commonly applied to ocular imaging analysis with fundus photography and optical coherence tomography (OCT) images.[21,22] Algorithms trained with DL have demonstrated expert or even above expert-level diagnostic accuracy for diabetic retinopathy, age-related macular degeneration (AMD), glaucoma, retinopathy of prematurity (ROP), refractive error especially myopia,[23] cataract, and anterior segment diseases.[24]

Artificial intelligence in myopia

Current potential artificial intelligence applications in myopia

The application of AI in myopia in children includes detection, prediction, and treatment [Table 1]. Based on the ocular appearance images, Yang *et al*.[25] built DL models that can be used for large-scale myopia screening in children, which could potentially relieve the burdens imposed by myopia. With baseline demographics and clinical variables such as age, spherical equivalent, AL, keratometry, and visual acuity, ML models have achieved robust performances for the prediction of childhood myopia progression and the onset of high myopia in later adulthood.[26-29] Foo *et al*.[30] were the first to use childhood fundus images to build DL models to predict the development of high myopia. Their models can used as a clinical assistive tool to identify "at-risk" children for early

Table 1: Artificial intelligence in myopia in children

Tasks	Authors and year	Main predictors	AI model	Aims	Main findings
Diagnosis and detection	Yang *et al*., 2020[25]	Ocular appearance images	DL	Large-scale myopia detection	AUC - 0.9270, sensitivity - 81.13%, specificity - 86.42%
Prediction	Lin *et al*., 2018[26]	Electronic health records: Age, SE, annual progression rate	ML	Predict the onset of high myopia over 10 years and at 18 years	High myopia over up to 10 years AUC: 3 years 0.874–0.976, 5 years 0.847–0.921, 8 years 0.802–0.886; high myopia by 18 years old AUC: 3 years 0.940–0.985, 5 years 0.856–0.901, 8 years 0.801–0.837
	Tang *et al*., 2020[27]	Demographics, SE, keratometry, WTW, CCT	ML	AL elongation prediction	Best model: Robust linear regression R2 0.87, 0.003–0.116 mm/year
	Yang *et al*., 2020[28]	Family history, gender, indoor and outdoor activities, axial length, keratometry	ML	Myopia prediction at 6th grade	AUC - 0.98, accuracy - 93%, sensitivity - 94%, specificity - 94%
	Li *et al*., 2022[29]	Uncorrected distance visual acuity, SE, AL, flat keratometry, gender and parental myopia	ML	Myopia progression for all 5 years	Combined weight of 77% and prediction accuracy over 80%
	Foo *et al*., 2023[30]	Retinal fundus imaging	DL	Prediction of the development of high myopia by teenage years	Image models AUC: 0.91–0.93, clinical models AUC: 0.93–0.94, mixed models AUC: 0.97–0.98
Treatment	Fang *et al*., 2022[31]	Age, baseline AL, pupil diameter, lens wearing time, time spent outdoors, time spent on near work, WTW, anterior corneal flat keratometry, posterior corneal astigmatism	ML	Predict the treatment effect of orthokeratology	C-statistic of the predictive model 0.821
	Fan *et al*., 2022[32]	Sex, age, horizontal visible iris diameter, spherical refraction, cylindrical refraction, eccentricity value, flat keratometry and steep keratometry readings, ACD, AL	ML	Estimating the alignment curve curvature in orthokeratology lens fitting	R^2 values for AC1K1, AC1K2 and AC2K1 values 0.91, 0.84, and 0.73
	Tang *et al*., 2021[33]	Corneal topographical maps	DL	Evaluation of corneal treatment zone after orthokeratology	Identified the treatment zone boundaries IoU of 0.90±0.06; identified the treatment zone centers average deviation 0.22±0.22 mm
	Wu *et al*., 2020[34]	Baseline IOP, recruitment duration, age, total duration and previous cumulative dosage	ML	Evaluating the effect of topical atropine use for myopia control on IOP	XGBoost is the best predictive model, and baseline IOP is the most accurate predictive factor

ML=Machine learning, DL=Deep learning, AUC=Area under the receiver operating characteristic curve, SE=Spherical equivalent, WTW=White to white, CCT=Central corneal thickness, AL=Axial length, ACD=Anterior chamber depth, IoU=Intersection over Union, IOP=Intraocular pressure, AI=Artificial intelligence

intervention. Furthermore, ML models utilizing corneal parameters and DL models based on corneal topographical maps have been able to evaluate the treatment of orthokeratology in children,[31-33] leading to more accurate lens fitting and individualized treatment planning.

In adults, the application of AI in myopia has been mainly focused on the detection and classification of high myopia, pathologic myopia, and myopia-related complications, including myopic maculopathy, MMD, myopic CNV, myopic tractional maculopathy, retinoschisis, macular hole, and retinal detachment [Table 2].

Most of these DL models were built based on fundus photographs,[35-37,39,41-44] while some were based on OCT images.[38,40,45-47] Notably, some of these DL models have achieved very powerful performances, even outperforming human experts in the detection of MMD and high myopia,[36] which suggests that the DL algorithms could potentially replace human graders in these tasks. DL models based on fundus photos or OCT images can also be used to predict refractive errors or high myopia,[48,49] which may facilitate the evaluation of myopia without overlooking the associated risks during ocular imaging assessment and potentially reduce the global burden of myopia. In addition, ML models have also been shown to be able to predict the surgical outcomes or complications of corneal and intraocular refractive surgery to correct myopia,[50,51] which can potentially be used as one of the preoperative assessment tools.

Advances in artificial intelligence technology for myopia

In addition to the above-mentioned ML and DL methods, there are emerging advances in AI technology which

Table 2: Artificial intelligence in myopia in adults

Tasks	Author (year)	Main predictors	AI model	Aims	Main findings
Diagnosis and detection	Lu *et al*., 2021[35]	Fundus images	DL	Detection of pathologic myopia	AUC - 0.979, accuracy - 0.963
	Tan *et al*., 2021[36]	Fundus images	DL	Detection of high myopia and MMD	Detection of high myopia: AUC - >0.913; detection of MMD: AUC - >0.969
	Lu *et al*., 2021[37]	Fundus images	DL	Detection of pathologic myopia, classification of myopic maculopathy	AUC - 0.995, accuracy - 97.36%, sensitivity - 93.92%, specificity - 98.19%
	Choi *et al*., 2021[38]	OCT images	DL	Detection of high myopia	AUC - 0.86–0.99
	Wan *et al*., 2021[39]	Fundus images	DL	Grade the risk of high myopia	AUC - 0.9968 for low-risk high myopia, AUC - 0.9964 for high-risk high myopia
	Li *et al*., 2022[40]	OCT images	DL	Detection of retinoschisis, macular hole, retinal detachment, mCNV	AUC - 0.961–0.999, sensitivity and specificity - >90%
	Tang *et al*., 2022[41]	Fundus images	DL	Grade myopic maculopathy, diagnose pathologic myopia, identify and segment myopia-related lesions	Grading accuracy - 0.9370, diagnosing pathologic myopia - 0.9980, segmentation model F1 values - 0.80–0.95
	Hemelings *et al*., 2021[42]	Fundus images	DL	Detection of pathologic myopia; fovea localisation; segmentation of optic disc, retinal atrophy and retinal detachment	Detection of pathologic myopia: AUC - 0.9867; foveal localisation: 58.27 pixels
	Rauf *et al*., 2021[43]	Fundus images	DL	Detection of pathologic myopia	AUC - 0.9845, accuracy - 95%
	Du *et al*., 2021[44]	Fundus images	DL	Detection of pathologic myopia and myopic maculopathy (diffuse atrophy, patchy atrophy, macular atrophy, mCNV)	Diffuse atrophy AUC - 0.970, sensitivity - 84.44%; patchy atrophy AUC - 0.978, sensitivity - 87.22%; macular atrophy AUC - 0.982, sensitivity - 85.10%; mCNV AUC - 0.881, sensitivity - 37.07%
	Du *et al*., 2021[45]	OCT images	DL	Detection of myopic maculopathy	mCNV AUC - 0.985; MTM AUC - 0.946; DSM AUC - 0.978
	Sogawa *et al*., 2020[46]	OCT images	DL	Detection of myopic macular lesions (mCNV, retinoschisis)	AUC - 0.970, sensitivity - 90.6%, specificity - 94.2%
	Ye *et al*., 2021[47]	OCT images	DL	Detection of myopic maculopathy	AUC - 0.927–0.974
Prediction	Varadarajan *et al*., 2018[48]	Fundus images	DL	Estimate refractive error	MAE - 0.56–0.91 diopters
	Yoo *et al*., 2022[49]	Posterior segment optical coherence tomography images	DL	Estimate uncorrected refractive error; detect high myopia	SE prediction: MAE 2.66 diopters; detect high myopia: AUC - 0.813, accuracy - 71.4%
Treatment	Shen *et al*., 2023[50]	ICL size, ACD, pupil size, ACA, CT, AL, etc.	ML	Predict the vault and the EVO-ICL size	Random forest R2=0.315, accuracy=0.828, AUC=0.765
	Kim *et al*., 2022[51]	Fundus photography, preoperative ACD, planned ablation thickness, age, preoperative CCT	ML	Identify high-risk patients for refractive regression	Combined model AUC=0.753, single model AUC=0.673

DL=Deep learning, ML=Machine learning, AUC=Area under the receiver operating characteristic curve, MMD=Myopic macular degeneration, OCT=Optical coherence tomography, mCNV=Myopia choroidal neovascularization, MTM=Myopic tractional maculopathy, DSM=Dome-shaped macula, MAE=Mean absolute error, ACD=Anterior chamber depth, CCT=Central corneal thickness, ACA=Anterior chamber angle, CT=Corneal thickness, AL=Axial length, AI=Artificial intelligence, ICL=Implantable collamer lens

include but are not limited to, multimodal AI models, explainable AI (XAI), automated ML (AutoML), federated learning (FL), blockchain technology, and synthetic AI technology such as generative adversarial networks (GANs) that have been applied to the field of ophthalmology and myopia.

With the increasing quantity and availability of biomedical data, including biometric data, refraction data, treatment response, and different modalities of ocular imaging data, this has allowed for multimodal AI solutions to capture the complexity of myopia. Foo *et al*.[30] developed the multimodal AI models based on fundus photographs and different clinical variables, which demonstrated good prediction of 5-year risk of developing high myopia in children.

One of the main barriers limiting the implementation of AI in the real world is the lack of explainability and the fear of its “black box” nature. The emergence of

XAI technology could potentially solve this barrier.[52,53] An XAI is one that produces details or reasons to make its functioning clear or easy to understand.[52] Studies have been done using an XAI framework for the diagnosis of macular diseases based on OCT images.[54] Further, in order to make ML techniques easier to apply and to reduce the demand for coding expertise, AutoML has emerged as a growing field that seeks to automatically select, compose, and parametrize ML models to achieve optimal performance on a given task or dataset.[55] Studies have been done with AutoML by ophthalmologists without coding experience to build a predictive model of proliferative vitreoretinopathy.[56] Moreover, FL is a promising approach to circumvent the need for large clinical datasets while preserving data privacy.[57] It is a distributed ML approach that aims to build comprehensive DL models without the need for a centralized database.[58] One of the successful applications of FL for multicentre collaboration in ophthalmology is in the improvement of classification performance in ROP.[59] However, to our knowledge, there have not been any studies using FL, XAI, and AutoML in myopia.

Blockchain technology offers a shared ledger for data management in a secure decentralized manner while preserving traceability when reporting results, addressing the concerns regarding privacy preservation during cross-institutional and cross-collaborator data transfer,[60,61] and facilitating the building of models by combining sensitive data from different sources to form larger training datasets.[62] Tan *et al*.[36] have demonstrated the implementation of a blockchain-based AI platform that enabled secure data sharing of fundus photographs and DL algorithms for myopia between China and Singapore, securely facilitating multinational cooperation. GANs are a set of deep neural network models used to generate synthetic data.[63] With its generative and discriminative features, GANs can be used to enhance the existing training datasets, which in turn optimizes parameters for improved image classification or segmentation while reducing patient identification risks to preserve data privacy.[64,65] In ophthalmology, GAN models have been built to synthesize fundus photos to improve the performance of classification and diagnosis of AMD,[65] glaucoma,[66] OCT images for retinal diseases,[67] and indocyanine green angiography images for lesion segmentation in high myopia.[68]

Digital Solutions for Myopia

Background

The simultaneous maturation of multiple digital and telecommunications technologies has created an unprecedented opportunity for the field of ophthalmology to adapt to new models of care using telehealth supported by digital innovations.[69] The scope of digital health is broad, with components such as AI, big data, cloud computing and analytics, electronic health records, mobile health (mHealth), wearables, and virtual or augmented reality (AR) tools, and these can be used to complement each other and supplement telehealth services. Despite many aspects of digital health, there has been a greater interest and focus on AI recently. However, other major elements of digital health, such as wearables, could also substantially assist in improving patient-centered care but this is an area that has yet to be fully explored.[70]

Digital solutions to myopia

Digital technology that has been applied to myopia includes digital therapeutics, self-monitoring devices and applications, virtual reality (VR) or AR technology, and wearable devices.

Digital therapeutics uses evidence-based software as therapeutic interventions, which has the potential to offer innovative treatment strategies for childhood myopia control beyond traditional treatment methods.[71] For example, SAT-001 is a software algorithm that modulates the level of neuronal–humoral factors and has been proposed to retard the progression of childhood myopia.[71] However, further clinical studies involving myopic children may be warranted to validate the proposed strategy. Although many digital therapeutics products and technologies are still in the early stages, with the increase of research and development efforts combined with results achieved through clinical evidence, this could potentially provide promising solutions to myopia.

Self-monitoring devices and applications, such as mHealth applications and web-based tools, are able to continuously monitor diseases remotely. For example, the SVOne, a portable Hartmann-Shack wavefront aberrometer that can be attached to a smartphone to examine the refractive error of the eye objectively,[72] has been shown to be able to provide measurements of refractive error that are similar to other subjective and objective methods. In addition, Wisse *et al*.[73] developed a web-based test that measures visual acuity and spherical and cylindrical refractive errors, which was comparable with the standard subjective refraction results. These applications can provide individualized frequent monitoring of patients' myopia status, building on the large database while providing an avenue to cultivate precision medicine in myopia.

VR is useful in assessing an individual's task performance by simulating environmental conditions and task types generated by computer graphics.[69] Currently, VR technology has been used to help detect visual field deficits in glaucoma patients,[74] and for the evaluation and treatment for strabismus and amblyopia.[75,76] With regard to myopia, there have been proposals that VR devices might be a possible approach to myopia control by maintaining peripheral defocus or simulating an outdoor environment.[77] Recently, researchers have also designed AR-based optical systems with peripheral defocus for myopia control.[78] Regarding the outcomes of these interventions, studies have shown that choroidal thickness markedly increased after wearing a VR headset in young adults.[79] However, further studies are warranted to determine whether this change could influence myopia progression in young adults.

Wearable devices such as Clouclip have been designed for myopia control, which are able to detect activity and light intensity exposure levels in children at risk of developing myopia. Wen *et al*.[80,81] evaluated the difference in daily behaviors between myopic and nonmyopic participants using Clouclip, and found that protective factors of myopia include exposure to greater light intensity for a longer time, and involvement in near-work activities at a further distance. Similarly, Cao *et al*.[82] reported that Clouclip could act as a potential strategy for managing myopia by encouraging the modification of unhealthy near-work behaviors in children.

Challenges and Future Directions

Challenges

There are several challenges to developing and implementing clinical AI and digital health tools for myopia. First, hesitance from public and governing bodies to accept AI and novel digital technology is common, given concerns of accountability, privacy, and safety.[83] This contributes to the difficulty in implementing these models in real-world clinical practices. As such, among the many innovations that have been described in this review, very few are used in daily clinical practice despite publication and validation.[84] Second, the lack of infrastructure support and resource limitations, especially in less developed regions, including poor Internet connectivity, and lack of eye care professionals with skills in digital health literacy, impede the adoption of new digital technologies. Third, AI and digital technology systems are often dependent on expensive hardware and software, such as high-resolution fundus cameras for image acquisition, GPUs for building DL algorithms, and VR/AR headsets or wearable devices. The direct and indirect costs imposed by the development, implementation, and maintenance of these equipment could also become significant barriers for less developed areas.[85] Fourth, there are concerns that the implementation of AI and digital technology could lead to potential risks for leaking private patient data. Enhancing cybersecurity protocols may be required to reduce these potential risks.

Future directions

Intensive collaborative research efforts and substantial investments will be necessary to overcome the challenges in the development and implementation of AI and digital tools for myopia. Establishing a global myopia consortium task force with nation-level representatives from different regions, including eyecare professionals and institutions, may facilitate organized coordination of efforts toward integrating these digital health tools into clinical workflows. Global collaboration may allow for large-scale prospective clinical and imaging data collection and creation of standardized datasets for developing AI models. Adequate funding and infrastructure support are critical for the development and implementation of AI and digital tools. Eye services need to be prioritized in national health policy planning and budgeting.[6,86] In addition to public health care policies, collaboration with nongovernmental organizations and private sector companies can also play a role to drive cost-effective eye care services to be available to the public. Development and implementation of AI systems with lower technical requirements, such as smartphone-based screening, may also serve as an initial economic tool to sieve patients through high-volume mass screening. Further research into privacy-preserving digital technology, including FL, blockchain technology, and GANs may help potentially strengthen AI models without compromising patient data confidentiality and ownership regulations, improving the public's confidence in AI and digital tools.

Conclusion

Emerging AI and digital technologies may have the potential to provide solutions to tackle the unmet needs in myopia through rapid, efficient data processing, automated detection for screening and risk stratification, individualized prediction and prognostication of myopia progression. AI applications in myopia in children and adults have been developed for the detection, diagnosis, and prediction of progression. Novel AI technologies, including multimodal AI, XAI, FL, AutoML, and blockchain, may further improve prediction, circumvent concerns of explainability, safety, and improve accessibility. Digital technology advancements include digital therapeutics, self-monitoring devices and applications, VR/AR technology, and wearable devices, which also provide possible avenues for monitoring myopia progression and control. However, there are still challenges in the implementation of these technologies into clinical practice, which include requirements for specific infrastructure and resources for set up, demonstrating clinically acceptable performance, and addressing concerns of accountability and safety of data management. Nevertheless, it remains an evolving field with the potential to address the growing global burden of myopia.

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Conflicts of interest

The authors declare that there are no conflicts of interests of this paper.

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