Bridging the vision gap: using AI-based smartphone apps ethically and strategically to increase access to visual impairment detection among children aged 0-5.

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Abstract

Visual impairment affects over 2.2 billion people globally, negatively influencing individuals' socioeconomic status and mental health. A significant proportion of these cases originates in early childhood. Amblyopia and its associated risk factors are the most common causes of visual impairment among children, causing permanent vision loss if untreated by the age of 6-10. Therefore, this paper focuses on early detection among children aged 0-5. Current screening practices, though effective, are inaccessible to many due to limitations caused by cost, geographic coverage, and the need for clinical environments. This paper explores existing AI-based solutions, evaluating their strengths and limitations. The most promising solution to revolutionize the early detection of visual impairment is to adopt AI-based smartphone apps for vision detection. By using deep learning to analyze facial videos and ocular movements, such apps offer high diagnostic accuracy with minimal cost and infrastructure. The paper further examines AI approaches to minimize the negative effects associated with visual impairment to help those with permanent vision loss or those experiencing long-term vision rehabilitation. Ethical and strategic considerations involved in the large-scale implementation of AI are addressed by suggesting the implementation of the Governance Structure proposed by Ben Shneiderman. Ultimately, this study argues that AI-powered smartphone apps can be a transformative tool for early detection of visual impairments, capable of democratizing access, especially among underserved populations.

Keywords: visual impairment, early detection, AI-based smartphone apps, ethical and strategic concerns

Introduction

According to the World Health Organization (2023), at least 2.2 billion people globally suffer from visual impairment, defined as when " an eye condition affects the visual system and its vision functions." This number means that one in every four people experiences visual impairment. However, at least 1 billion of the cases could have been prevented. The causes of this widespread problem have yet to be well addressed, and the global population has made limited efforts in detecting and preventing visual impairment.

Causes and Influential Factors

Causes of visual impairments vary and may differ significantly according to age and location. One of the most common causes is refractive errors, which occur when one's eye is unable to bend light properly, preventing light from focusing correctly on the retina. Refractive errors include myopia (nearsightedness) and hyperopia (farsightedness), with a prevalence of 77.20% among all people, as suggested by a study summarizing findings from more than 5000 papers covering a wide range of countries (Khabazkhoob et al., 2022). Although affecting a significant proportion of global society, this visual problem can be easily solved with eyeglasses or contact lenses. Given their ease of resolution, refractive errors have not been included in population-based surveys; thus, people with this type of visual impairment are excluded from the total count of 2.2 billion people (World Health Organization, 2019).

Many other eye diseases, however, can lead to irreversible visual damage if not prevented in time, which highlights the necessity of early detection among children. Within this population, the most common cause of visual impairment globally is amblyopia, "a disorder characterized by abnormal processing of visual images in the brain during a critical period of vision development, resulting in a functional reduction of visual acuity" (Chou et al., 2011). With no considerable differences between geographical areas, amblyopia affects

2% to 4% of children worldwide (Blair et al., 2020). Strabismus, a misalignment of the eyes, is the most common risk factor for amblyopia, affecting 0.14% to 5.65% of children globally (Hashemi et al., 2019). Refractive errors can also potentially result in amblyopia. Left untreated, amblyopia is unlikely to resolve spontaneously and is highly likely to cause lifelong visual impairment.

The fundamental causes of eye diseases include genetic and environmental elements. Genes may be the most influential factor. A study done by Wojciechowski (2010) has shown that nearly 60% to 90% of individual variance in refractive errors can be attributed to genetic factors. Therefore, children whose parents are visually impaired are more likely to experience some kind of eye condition. A child's living environment is another critical aspect affecting the development of vision. One factor is diet. Nutrition in certain foods is a key component to the development of the eyes. The Age-Related Eye Disease Study Research Group conducted a multi-site clinical study in 2001, proving that antioxidants, including vitamins, omega-3 fatty acids, and carotenoids, contribute significantly to preventing eye diseases. For example, a combination of zinc and antioxidants reduces age-related macular degeneration by 25% and severe vision loss by 19% among those at high risk. Consuming food rich in these nutrients, such as spinach and fish, enhances eye development, while deficiencies in diets will elevate the risks of visual impairment (Seddon, 2013).

Socioeconomic factors, including educational attainment, employment, and wealth, may act as external factors in addition to genetic and environmental elements that influence vision health. For instance, analyzing a nationally representative sample of US residents, Chiu-Fang Chou et al. (2015) concluded that students with only a high school diploma were 21% more likely to have visual impairments compared to those with higher educational attainment. That percentage rises to 31% for those who did not complete high school. This indicates a negative correlation between education level and visual impairment. Low

educational attainment is linked to adverse socioeconomic position. Poorly educated individuals may be restricted by economic concerns from accessing healthcare services for vision detection and treatment.

Wang et al.'s cross-sectional study further shows the association between visual impairment and socioeconomic status (2017). They considered the Human Development Index (HDI) as a reflection of socioeconomic level, observing that the prevalence of moderate to severe visual impairment reduced from 4.38% in low-HDI regions to 1.51% in high-HDI regions, highlighting that the prevalence of visually impaired people decreases among people with higher socioeconomic status. This relationship is largely due to the ability to access healthcare resources. People of lower socioeconomic status have lower wealth levels, which limits their access to preventive care and vision examinations. According to Cumberland and Rahi (2016), people of low socioeconomic status are also restricted from purchasing eyeglasses when experiencing refractive errors, which may lead to deterioration and further eye diseases such as amblyopia.

Influences

Visual impairment is not only influenced by socioeconomic factors but can also cause negative consequences that further impede development in socioeconomic status. Visually impaired students are shown to face additional difficulties in learning, as reflected by enrollment rates. Wodon et al.'s study in 2018 revealed that only a minority of visually impaired students were enrolled in school in South Africa, with percentages of 46.4% and 31.5% in Senegal and Zambia, respectively.

Such low enrollment rates can be largely attributed to the lack of educational resources and schools targeted at these students, especially in developing countries like South Africa. Most students are thus offered only two choices: drop out of school or attend mainstream schools. In mainstream schools, however, these students are forced to study with

normally sighted peers who lack knowledge of visual impairment. The learning process in such schools also relies heavily on vision. By contrast, schools designed for visually impaired students offer lessons that stimulate auditory and tactile senses to enhance their understanding. This disparity is crucial when studying abstract concepts related to graphs and figures, during which the teachers may neglect the special learning needs of visually impaired students and fail to provide clear explanations. The inability to see properly creates significant barriers to learning, thus causing visually impaired students to be disadvantaged compared to their peers in competing for opportunities for higher education attainment.

Individuals who lack the expertise in certain fields of study that is gained through exploration in educational stages beyond high school are seen as having low competence when they seek occupation, and thus face high risks of unemployment. According to Cumberland and Rahi (2016), “reduced visual function was independently associated with increased risk of being unable to work and being unemployed.” Visually impaired people are shown to be twice as likely to be unemployed compared to the normally sighted. Even those employed may face additional daily challenges at the workplace, which result in low productivity. For instance, visually impaired employees often require more time to read emails or reports, causing them to fall behind in completing tasks. The annual cost of productivity loss for uncorrected myopia, one of the least severe visual impairments, was estimated to be 244 billion US dollars globally (World Health Organization, 2019). These consequences lead to financial burdens, restricting visually impaired people from enhancing their wealth and improving their living standards. This problem, centered on visual impairment, becomes a cycle that is highly likely to influence new generations negatively.

Because they limit people from pursuing educational studies and favorable living conditions, visual impairments should not be examined as simple physiological defects. They can further cause harm to mental health, especially for adults and the elderly. In Zhang et al.’s

study, 10.7% of visually impaired adults reported a significant extent of depression, which is 3.9% higher than the normally sighted (2013). The negative feelings may be a result of continuous unpleasant experiences in schools and workplaces. As visually impaired people endure such feelings for long periods in life, they experience a decline in physical health standards. Jacobs et al.(2005) show that visually impaired elders present poor self-rated health, increased frequency of visiting hospitals, and elevated risks of death.

Visual impairments are in urgent need of being addressed globally because they are correlated with negative influences in different aspects of every stage of life. The key to breaking the cycle that limits the living quality of visually impaired people is to tackle its basis, resolving visual impairment fundamentally. Specifically, early detection among children is needed to prevent the vision deterioration that potentially leads to permanent impairment. Because amblyopia and its associated risks have been widely acknowledged to become irreversible when children reach the age of 6-10 (Chou et al., 2011), this paper focuses on vision detection from ages 0-5. Solutions to minimize the negative influences of visual impairment are also explored in consideration of those with permanent impairment or experiencing long-term treatment.

Current Clinical Practices

Efforts have already been made to address the problem of visual impairment. In the following section, existing solutions are categorized into two groups: Group 1 incorporates practices to detect and treat visual impairment, and Group 2 incorporates practices to address the negative consequences associated with visual impairment.

Group 1

Current methods to detect visual impairment vary depending on age. This is due to both the variance of causes according to age and the effectiveness for the targeted age group. For instance, for children aged 0 to 1, parents are responsible for observing vision

development in daily life. If their child is unable to achieve certain milestones, it would be best for them to refer their child to primary care centers. This is a standard proposed by the National Center for Children's Vision and Eye Health (NCCVEH), a trusted organization funded and supported by the U.S. Department of Health and Human Services (*Vision Screening Guidelines by Age*, 2020). The NCCVEH also holds parents responsible for children's early vision detection from ages 0-5.

Once children reach the age of 1-2 years old, screening using instrument-based tools, also referred to as photoscreening, is recommended by the NCCVEH. Specifically, clinicians use technical tools such as infrared cameras to capture and analyze images of patients' eyes. If clinicians detect abnormalities in children's eyes, parents are advised to rescreen as soon as possible and initiate a referral if necessary. This testing process only involves taking photographs, which can be done in a few seconds and is thus efficient in terms of time. Photoscreening of images has high objectivity and detection accuracy. Efstathia Kiatos et al. (2020) tested the effectiveness of photoscreening in Ontario, Canada, with 5,959 children, among whom 2,496 were less than 3 years old. Using hand-held photoscreeners, volunteers were able to conduct photoscreening testing with only 1.5% untestable for those under the age of three. In addition, the referral rate, the percentage of children suggested to be transferred to medical centers for further examination, is consistent with other studies related to photoscreening. Therefore, photoscreening is particularly useful for toddlers within this age range.

However, this approach has its limitations. Photoscreening has yet to be well developed in healthcare systems around the world; its positive influences are therefore constricted. Chou et al. (2011) reported that usage of photoscreeners among pediatricians is less than 10%. This can largely be attributed to the high financial cost of the instruments. Horwood et al. (2020) reviewed 370 research papers and concluded that evidence of the

cost-effectiveness of photoscreening compared to traditional visual acuity screening is lacking. In addition, the images taken by volunteers must be analyzed by medical experts or reading centers, raising the problem of differences in expert interpretations due to individual subjectivity, image quality, and patient background. In addition, although photoscreening reduces testing time, parents may have to wait for a long time before being aware of their children's eye circumstances, which may slow down the process of visual impairment prevention. However, photoscreening is the most suitable practice for toddlers at this age because they are often poorly cooperative due to underdeveloped cognition, and using instruments for screening does not require the children's cooperation. The limitations of photoscreening highlight a significant gap in a widely accessible and effective screening approach among toddlers aged 1-2.

Children three to five years old experience preschool vision screening. The NCCEVH recommends photoscreening or standardized vision measurement tests, which usually involve eye charts (*Vision Screening Guidelines by Age*, 2020). These tests are frequently offered in primary care and community-based settings, and they aim to measure visual acuity, conducted through standardized tests such as the Snellen Eye Chart and the Tumbling E (Chou et al., 2011). Along with assessments of strabismus and stereoacuity (the ability to perceive depth), this method helps identify visual disabilities, raising awareness for families about when it would be appropriate to seek medical care centers for further evaluation. Therefore, in an ideal case, it can be effective in contributing to the detection of nearly all causes of visual impairment. Conducting a longitudinal study with 3126 Swedish children, Kvarnström et al. (2001) show that preschool visual screening combined with treatment after detection resulted in a reduction in the prevalence of amblyopia, ranging from 2% to 0.2%. This finding demonstrates the effectiveness of screening methods in detecting and preventing amblyopia.

This approach is appropriate for preschoolers aged three to five because they have generally developed a comprehensive cognition of their surroundings, and tend to be cooperative in standardized measurements. In special cases where children are poorly cooperative, instrument-based screening methods can also be adopted. Using standardized tests excels in its cost-effectiveness, as limited instruments are required to conduct the tests. Therefore, experts and the United States Preventive Services Task Force (USPSTF) agreed in line with the NCCEVH to use this type of vision screening for children aged between three to five (Chou et al., 2011). However, even within the suggested age range, preschool vision screening's current prevalence is in question. According to a national survey of U.S. pediatricians, only one-third of children aged three years reported receiving visual acuity screening. Even though that percentage rises to 70% for children aged four or five years, a considerable number of children who do not receive these tests are still vulnerable to visual impairments (Chou et al., 2011).

As for treating amblyopia, occlusion—reducing or eliminating the visual suppressive effect of the nonamblyopic eye through patching—has been recognized as the gold standard throughout history. Using atropine drops or surgeries after cessation of amblyopia treatment are also traditional methods. Although new methods involving technology have been proposed recently, there is little evidence of their effectiveness exceeding that of previously recognized approaches. As stated by Meier & Tarczy-Hornoch (2022), "It is still unclear whether [newly suggested] treatments are superior to traditional, low-cost treatment methods or whether their therapeutic mechanisms are fundamentally different from those of established treatments." Therefore, the treatments of amblyopia and its associated risk factors are not further discussed in this paper.

Group 2

Efforts have also been made to compensate for the negative influences caused by visual impairments. The “Chinese Online School for the Blind” (COSB) is an example of solutions targeted at improving educational circumstances for visually impaired students. This educational platform offers online courses taught by student or teacher volunteers. Lessons are taught with assistive devices that parents can easily replicate with materials at home. This method can significantly enhance teaching efficiency by incorporating tactile senses, thus providing effective learning resources for visually impaired students (Yu et al., 2025). Although demonstrating a promising approach, this platform is only in its early phase, with limited volunteers and courses. It needs years of development before a considerable number of visually impaired students in its targeted areas can benefit. Moreover, to adopt this approach globally, governments would have to establish different platforms to provide courses in their corresponding language, which is a time-consuming task.

Other solutions aiming to solve mental health problems caused by poor vision, however, are shown to be immediately effective. Specifically, multiple intervention strategies, including self-management, problem-solving, cognitive behavioral, and stepped care, have been proven beneficial (Demmin & Silverstein, 2020). Although reducing depression levels, these interventions are unable to resolve educational and financial issues related to visual impairments. To fully address every negative impact, solving the problem at its source from the medical perspective, by preventing and treating visual impairments, is seemingly the fundamental solution. Indeed, this ultimate solution needs to be specified, for the cause of visual impairments varies, and may significantly differ across age groups and territories.

The solutions in Group 2 are effective for those with irreversible visual impairment. However, to target the problem at the source, enhancing detection efficiency to prevent or reduce visual impairment is the key to providing a promising future for the visually impaired population.

Artificial Intelligence Solutions

Artificial Intelligence (AI), with distinct and advanced capabilities to learn from large datasets efficiently and perform tasks consistently without burnout, has been widely proposed to address the limitations of current vision screening practices among children aged 0-5. According to Asan et al. (2020), AI has great potential to be implemented in "clinical data interpretation, clinical trial participation, image-based diagnosis, preliminary diagnosis, virtual nursing, and connected healthcare devices." Excelling in all these areas, artificial intelligence offers numerous possibilities for the early detection of amblyopia and its associated risks and for addressing the negative impacts caused by visual impairment. Many attempts have already been made to address the problems. In the following section, solutions will be categorized into Group 1 and Group 2 in the same manner as in the **Current Clinical Practices** section

Group 1

Generative AI for Enhancing Patient Education about Visual Impairment

Initially, parents must realize the importance of vision screening for their children to adopt vision screening practices. The Internet, having developed in recent years and become an easily accessible platform to acquire information, can contribute to expanding parents' knowledge of eye diseases, specifically, amblyopia and its associated risk factors. Parents can simply input certain prompts in search engines such as Google to read sources of relevant information. However, generative AI, most famously exemplified by ChatGPT, may even enhance the efficiency of conveying key information. It can extract content from various sources to provide a summary so that parents can understand it easily. This is the first way that AI can be used.

Researchers have tested the accuracy and correctness of AI-generated content. Wu et al. (2024) determined this by comparing ChatGPT-3.5's adherence to the guidelines of

amblyopia from “the American Association for Pediatric Ophthalmology and Strabismus (AAPOS),” a recognized and trusted organization. ChatGPT showed a response using 42% of keywords from AAPOS, excelling Google Assistant, a voice-based virtual assistant, with an adherence rate of 31%. Responses from ChatGPT also had similar reading levels to the guidelines from AAPOS. Therefore, advanced generative AI may respond with more sentences and terms recognized by official organizations, thus showing higher accuracy in its generated content compared to former tools like virtual assistants.

This finding, however, is insufficient to support widespread acceptance of generative AI as a tool to educate patients on all aspects of visual impairment. Adhering to official documents fails to show the correctness and effectiveness of the response. Fortunately, the two aspects have been evaluated by recent studies. Cappellani et al. (2024) targeted associated factors of amblyopia, such as strabismus, and asked ChatGPT-3.5 three questions: “What is X?”; “How is X diagnosed?”; and “How is X treated?”. Their evaluation metric was a number score: +2 as the highest, representing correct and complete; -3 as the lowest, representing wrong or potentially harmful. After comparing each response to the guidelines proposed by the American Academy of Ophthalmology (AAO), another trusted organization, they concluded that 77.5% of all responses were above +1. This indicates that a majority of the generative text was mostly accurate and helpful for patient education.

On the other hand, 22.5% of the responses received a score below -1, demonstrating that some content could mislead patients with incorrect or harmful information, which could significantly restrict their children’s opportunity to receive vision screening in time. This issue can be resolved, however, given the assumption that AI systems are continuously trained on more data and development. ChatGPT has already evolved into versions beyond 3.5. Developers can fine-tune their training data so that the AI model values information from trustworthy sources and official guidelines. As generative AI further advances, the

correctness and helpfulness of its responses will significantly elevate, thus becoming an essential tool for patient education. However, sometimes advancements produce worse results, and there is no guarantee of an upgrade in answer correctness. More research and validation are needed before widely acknowledging Generative AI for patient education on amblyopia and its associated risks.

Incorporating AI for Result Analysis in Standardized Vision Measurement Tests at Primary Care Centers

Once parents acquire information on visual impairment, such as the causes, symptoms, and influences of amblyopia, they are likely to follow recommended standards and take their children to primary care centers for vision screening. Traditional methods of vision acuity measurements are effective, but AI may further improve detection accuracy with its ability to organize and analyze test results. This is the second way that AI can be used. For example, Csizek et al. (2023) developed the "EuvisionTab Stereovision Test" (ETS), a new standardized vision measurement method in which children are shown images with random dots while wearing red-green goggles. Because the researchers did not know what combinations of dot density, motion, and noise would maximize the effectiveness of ETS, they used AI to combine four ETS versions with optimal performance and assigned each version a respective weight. By analyzing children's responses to all four ETS versions, the AI calculated a single score to indicate diagnostic results of amblyopia, strabismus, and refractive errors.

According to Csizek et al. (2023), "the AI-enhanced ETS achieved much higher accuracy than most classic tests for detecting amblyopia and its risk factors." Specifically, detection accuracy was measured based on the "Area under the receiver operating characteristic Curve" (AUC), an evaluation metric for the accuracy of a binary classification model. An AUC of 1 indicates perfect classification, and an AUC of 0.5 indicates pure

guesswork. Sensitivity, a metric for determining the proportion of correctly detected positives, and specificity, a metric for determining the proportion of correctly detected negatives, were also incorporated. The AUC reached roughly 0.91, while the sensitivity and specificity achieved 96% and 98%, respectively. Such high results in all three metrics indicate that the AI-enhanced ETS was able to conduct vision screening at an advanced level.

This study suggests that the approach of combining AI with screening practices at primary care centers can potentially show similar outcomes due to AI's ability to analyze data efficiently. Provided with sufficient training data, AI can interpret children's responses to stimuli in vision measurement tests and perform calculations according to the optimal formula. In addition, it can work consistently without burnout, excelling human clinicians in working efficiency. However, using AI in this way is not without limitations and drawbacks. AI functions primarily as an assistant for clinicians in conducting traditional screening practices; standardized vision acuity measurements remain the central aspect, requiring active participation from children. Therefore, implementing AI in this way fails to address the existing limitation of insufficient accessibility among toddlers and infants under three years of age.

Nevertheless, such attempts demonstrate AI's ability to achieve high detection accuracy even when conducting analysis and evaluation independently. Clinicians may no longer be the only source of vision detection that children and parents can rely on. These implications led to the development of AI in photoscreening, using AI as an independent diagnosis tool.

Involving AI in Photoscreening (Photo Analysis) at Primary Care Centers

AI-based photo analysis models have already been developed and tested. Shu et al. (2024) used smartphones to take 1419 facial photos from 476 individuals under standardized lighting conditions from a fixed distance in the clinic room. A deep-learning-based AI was

trained and validated using the photos to identify three associated risks of amblyopia: strabismus, myopia, and ptosis. The AI model achieved an accuracy of over 0.8 and an AUC exceeding 0.83 for all three eye diseases, presenting itself as a reasonably reliable vision detection system.

Shu et al. (2024) also analyzed AI's performance across age groups, separating participants into three subgroups: (1) individuals aged 0-5 years, (2) individuals aged 6-12 years, and (3) individuals aged 13-18 years. The first subgroup received the lowest sensitivity of 0.67, indicating that AI was deficient in identifying eye diseases among children 0 to 5 years old, a time period during which they are most vulnerable to amblyopia and its risk factors.

This result can be partially attributed to the data collection process. Participants were given various instructions, including "to remove their spectacles, maintain their head upright, and stare straight ahead." Children aged 0 to 5, especially infants and toddlers, are often less cooperative compared to those older and more mature. Poorly cooperative individuals may be reluctant to follow these procedures, causing experimenters to take low-quality photos, which would limit the AI model from identifying abnormalities in the images. In addition, Shu et al. (2024) took only one photograph per individual. This practice not only prevented them from replacing low-quality images but also prevented the AI model from analyzing eye movements and changes in facial expressions, which could contain much more useful information and indicators of abnormalities compared to single photos. The experimenters acknowledged this problem by proposing that "collecting patients' images from various perspectives can enhance the algorithm's performance".

Shu et al.'s study implies multiple significant insights on the improvements of implementing AI in photoscreening. Initially, to ensure that the material for analysis is of high quality, the model may need to take multiple pictures from different angles over a time

period, or simply record videos to capture more information in patients' eyes. The recordings also have to be clear for accurate evaluation results; thus, the model must alert the users of low-quality recordings so that they can collect new data. To target uncooperative infants and toddlers, AI developers need to approach them with attractions for them to focus on, which would simplify the process of acquiring high-quality videos for analysis.

Using AI-based Smartphone Apps, which Provide Analysis Based on Recorded Videos

Chen et al. (2023) demonstrated an approach that significantly enhanced accessibility by introducing an AI-based smartphone app named Apollo Infant Sight (AIS), which functions as follows:

(1) AIS provides users with guidelines for completing standardized preparations.

(2) AIS plays cartoon-like video stimuli while recording videos to capture phenotypic features, including facial appearance and ocular movements.

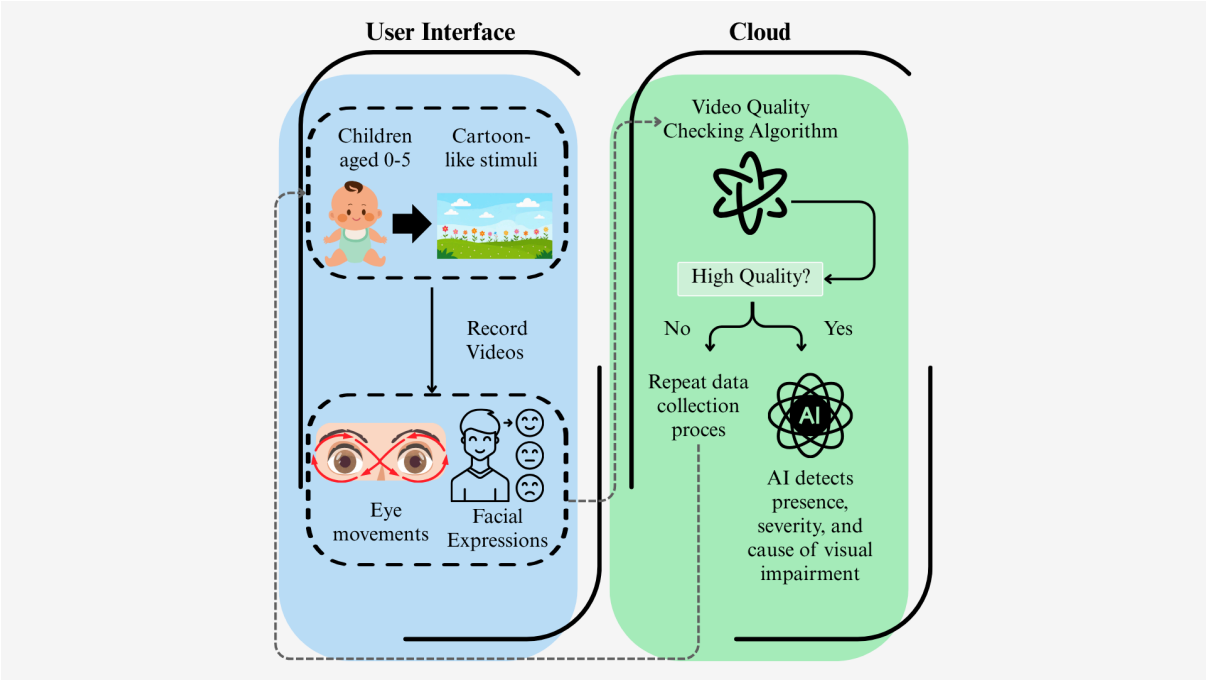
(3) A series of algorithms is applied to check the quality of recordings by discerning key facial points, recommending that the users collect new data when the videos are considered low-quality.

(4) A deep-learning detection model in the AIS analyzes these clips to identify visual abnormalities.

Figure 1 shows the workflow of the AI-based smartphone app AIS.

Figure 1

Workflow of proposed AI-based smartphone apps



Note. The process of children watching cartoon-like stimuli and the app recording videos is categorized as a procedure in the user interface. Video quality checking and visual impairment detection are classified as procedures in the cloud.

Using this app, parents no longer have to take their children to primary care centers for photoscreening; instead, the detection process can be done at home or in any setting. The proposed wide range of applications, however, is accompanied by potential variations in detection accuracy. Chen et al. (2023) recruited 3652 children aged under 4, taking 3865 videos and nearly 26 million images to test the performance of AIS in (1) clinical settings with trained volunteers and (2) home settings with untrained parents. In setting 1, AIS achieved an AUC of 0.843 during external validation (an independent dataset was used for evaluation). The validation process did not merely focus on whether AIS could detect abnormalities, but also examined whether it could distinguish the severity levels of visual impairment. AIS showed an AUC of 0.833 and 0.859 for comparison of mild and severe visual impairment with non-impairment, respectively, in external validation. In addition, the test evaluated whether AIS could recognize 16 common eye diseases among children, which

include risk factors of amblyopia, such as strabismus. It turned out that the AUC of all conditions except one exceeded 0.8. These results indicate that AIS has advanced abilities in identifying visual impairment and distinguishing the severity and cause in clinical situations.

In setting 2, AIS achieved an AUC of 0.859 in external validation, as well as 0.846 and 0.873 in mild and severe visual impairment level measurements. The researchers did not test AIS's ability to discern the 16 eye conditions in this case. Nevertheless, with consistent AUCs over 0.8, the deep-learning-based AI model in AIS presents relatively high accuracy in detecting the presence and severity of visual impairment. Although AIS's ability to discern different causes needs further evaluation, the current validation outcomes demonstrate the high accuracy and stability of AIS. AI-based smartphone apps have huge potential to revolutionize vision screening practices and address the under-coverage limitations of traditional approaches. Toddlers and infants can be effectively screened, and individuals from low socioeconomic backgrounds can also access screening, as smartphones have become increasingly prevalent even among socioeconomically disadvantaged populations in modern society. Therefore, incorporating AI in smartphone apps for visual screening is the most promising approach to enhance the efficiency of and increase access to visual impairment detection.

Highly effective AI tools can earn the recognition of authoritative organizations. In the field of visual impairment detection, the IDx-DR, a completely autonomous photoscreening AI for identifying diabetic retinopathy, exemplifies this possibility. Abràmoff et al. (2018) launched a multi-site study in primary care clinics to test the performance of IDx-DR. It achieved a sensitivity of 87.2%, a specificity of 90.7%, and an imageability rate, which measures the percentage of cases in which the model successfully captures and analyzes patient images to produce a valid result, of 96.1%. Based on its advanced capabilities confirmed by the validation process, the US Food and Drug Administration

(FDA) authorized it for use among healthcare providers for the automatic detection of diabetic retinopathy. This authorization significantly enhanced the implementation of IDx-DR, as the FDA conveys a sense of trustworthiness to the government, healthcare centers, and the general public.

This example shows that AI-based tools for detecting visual impairment, especially photoscreening tools, have high potential for receiving authorization from trusted organizations. The prerequisite, however, is a comprehensive evaluation process to ensure advanced and stable performance. The AIS has already achieved a relatively high standard in its diagnostic results. It has an even more advanced ability to detect multiple common eye diseases in children rather than focusing on one specific condition. Therefore, with further AI training and improvements in its detection accuracy, the AIS and other smartphone apps with similar functions are highly likely to be authorized for large-scale implementation.

Group 2

The solutions above can only target those with undeveloped visual impairment. For individuals experiencing permanent vision loss or undergoing long-term treatments, AI can offer assistance in addressing the negative consequences associated with visual impairment.

Implementing AI-based Smartphone Apps for Text-to-Speech Functions, Helping Visually Impaired Students with Education

Solutions incorporating AI have been proposed to compensate for the learning deficiencies experienced by visually impaired students. One essential aspect is providing personalized support to ensure that learning materials are accessible and understandable. Natural language processing (NLP), “a subfield of computer science and artificial intelligence (AI) that uses machine learning to enable computers to understand and communicate with human language” (Stryker & Holdsworth, 2024), can be used for this purpose. One of the

most important educational tools for these students, the text-to-speech (TTS) system, is heavily dependent on NLP to read aloud written content (Eziamaka et al., 2024).

TTS can help visually impaired students learn content from textbooks through the auditory senses, thus shifting the reliance on vision in the learning process. TTS can be applied in smartphone apps. For example, Jagadish et al. (2024), a team from the Raghu Institute of Technology in India, developed an Android app that incorporates trained AI models to function partially as text readers. Although they have not conducted validation tests on a wide scope, this smartphone app approach shows potential for presenting advantages similar to formerly discussed detection models like the AIS. They are easily accessible. Most people in this world, even those in undeveloped areas, have a phone. They only have to download the app and follow prompts to benefit from TTS with minimal financial cost.

However, one major limitation of a TTS system is the inability to describe images and graphs. This restricts its application to concepts related to figures. In addition, for widespread implementation of such apps, comprehensive tests on effectiveness in different areas, with consideration of various external factors, must be underscored.

Combining AI with Devices to Support Visually Impaired People with Day-to-Day Tasks

Other solutions aim to help visually impaired people with their daily lives, such as completing day-to-day tasks. Many of these solutions involve a practical product or device. Al-Muqbali et al. (2020) created a smart stick, combining AI with a walking stick to provide support in navigating surroundings. Specifically, a camera-based machine learning model is integrated into the stick, enabling it to identify faces and people, detect objects, and recognize colors. The AI model can provide audio feedback to enhance visually impaired people's cognition of the environment, which ensures safety by protecting them from running into people or objects. This further strengthens their ability to be a part of a collective group,

whether with classmates at school or with coworkers at workplaces, instead of being isolated at home.

However, this type of integration has limited prospects of large-scale application, as it is necessary to develop a large number of devices to respond to the vast demand of visually impaired people in society. The cost may also be problematic because the AI model needs to be incorporated into each device, whether a smart stick as demonstrated by Al-Muqbali et al. (2020), or products in different forms.

Summary

The strengths and limitations of AI-based solutions demonstrated above are summarized in Table 1.

Table 1

Summary of potential AI solutions for visually impaired people

Number	Approach	Group	Strengths	Limitations
1	Generative AI for enhancing patient education about visual impairment	1	- Efficient in providing information and a summary of multiple sources. - Able to answer personalized questions - Low financial cost	- Wrong answers can mislead users, with the possibility of restricting early detection of visual impairment.
2	Incorporating AI for result analysis in standardized vision measurement tests at primary care centers.	1	- Increases the productivity of testing - Elevates detection accuracy	- Undercoverage among toddlers and infants aged less than three
3	Involving AI in photoscreening (photo analysis) at primary care centers.	1	- Targets the entire population of children aged 0-5 - High accuracy in detecting multiple eye conditions	- Fails to consider multiple factors, such as eye movements - Cannot ensure the quality of the photo, especially

				for uncooperative children
4	Using AI-based smartphone apps, which provide analysis based on recorded videos	1	- Targets the entire population of children aged 0-5 - High accuracy in detecting both severity and specific eye diseases - Easily accessible with minimal cost - Enables detection at locations beyond primary care centers - Ensures the quality of collected data by attracting children with cartoon-like videos	- Limited evaluation for large-scale implementation - Detection accuracy can be further enhanced
5	Implementing AI-based smartphone apps for text-to-speech functions, helping visually impaired students with education	2	- Easily accessible with minimal cost - Reduces reliance on vision in the learning process	- Limited evaluation for large-scale implementation - Unable to address issues in completing daily tasks
6	Combining AI with devices to support visually impaired people with day-to-day tasks.	2	- Helps navigate their surroundings with audio feedback - Supports them to be a part of a collective group	- High financial cost - Unable to be provided to a vast number of customers in an efficient manner

Note. The table presents six AI-based solutions, with the first four targeting early detection of visual impairment and the latter two targeting resolving the negative consequences associated with visual impairment. The strengths and limitations of each solution are discussed.

Among the solutions incorporating AI shown in Table 1, number 4, using AI-based smartphone apps to detect amblyopia and its associated risks, is the most promising approach to revolutionizing visual impairment prevention among children aged 0-5. Using such apps could enable parents or caregivers to conduct vision screening at a low cost without reaching

out to clinicians in primary care centers, ensuring wide accessibility to resolve the significant under-coverage of traditional vision screening approaches. In addition, the design of the smartphone app corresponds with the human-centered AI (HCAI) ideal proposed by Ben Shneiderman (2022), which highlights humans' central position in the implementation of AI. HCAI is most effective in maximizing human benefits.

Shneiderman defines HCAI from two dimensions: process and product. The approach of AIS achieves the expectations of HCAI in both.

(1) Process: HCAI is expected to be designed based on user experience; included aspects are "user observation, stakeholder engagement, usability testing, iterative refinement, and continuing evaluation of human performance" (Shneiderman, 2022). The AI-based smartphone app approach, such as AIS, exemplifies this dimension comprehensively. The research team engaged both trained professionals and untrained parents, key stakeholders in early vision detection, through testing in clinical and home environments. User observation and iterative refinement are apparent in the system's quality control algorithms, which detect poor video recordings and prompt users to collect new data. Usability was prioritized by providing clear instructions to parents for video collection. Additionally, the system underwent continuous evaluation through a large-scale study involving over 3,600 children, enabling the developers to assess and enhance AIS's performance. These efforts demonstrate a systematic commitment to the process dimension of HCAI design.

(2) Product: Regarding the design process of HCAI, "the goal is to create products and services that amplify, augment, empower, and enhance human performance" (Shneiderman, 2022). In addition, HCAI products should provide a high extent of both automation and human control. The smartphone app fulfills the product dimension by functioning as a supertool, a design metaphor suggested by

Shneiderman. A supertool refers to an AI system that "augments human abilities, empowers users, and enhances human performance". The smartphone app empowers inexperienced parents to perform advanced vision screening tasks, enhancing human abilities by guiding standardized procedures. At the same time, the app performs complex diagnoses automatically using deep learning systems. The app achieves high human control because humans retain the choice of when and where to conduct screening. In addition, children would be recommended for referral to pediatric care centers for further analysis by clinicians. Thus, the prevention and treatment plan are entirely determined by clinicians. Humans retain high control.

This human-centered design of AI-based smartphone apps elevates their potential to revolutionize vision screening practices. However, no system is without limitations. One key constraint is the interpretability of AI decisions. Although users have high control over when and where to conduct photoscreening with the app, the diagnostic process is highly automated. Especially when using complex models such as deep learning, AI would not be able to present explanations for its outcomes. Therefore, the smartphone app would be unable to inform users and clinicians of the evidence for the suggested detection result. If the app provides a wrong diagnosis, clinicians may need to conduct multiple comprehensive tests on children to determine the specific cause of visual impairment. This is because detection approaches vary when clinicians aim to identify a specific cause, unlike the general approaches to recognized visual impairment. The limited transparency in AI may limit the efficiency of verifying its diagnostic results in pediatric care settings.

In addition, the performance of the AI system is heavily dependent on high-quality user data. If the data is biased, incomplete, or contextually narrow, the system's recommendations may inadvertently reinforce existing inequities. This is an example of algorithmic bias, which will be further discussed in the following section. Users would not be

able to identify or resolve this bias due to the AI's highly automated diagnostic process. While the iterative design process supports continual improvement, the smartphone app may not fully capture the needs of marginalized or less-represented user groups unless explicitly prioritized. The risk of algorithmic bias highlights the need for continuous validation of the AI's performance across the intended area of implementation.

When considering a large-scale implementation of AI-based smartphone apps, strategic and ethical issues need to be thoroughly processed to prevent any related additional consequences.

Ethical and Strategic Considerations

A wide range of stakeholders are involved in implementing the smartphone apps. Those involved include:

(1) App developers: A vast number of potential users will significantly increase the demand for stable and accurate detection. Therefore, app developers will have a greater responsibility to continuously enhance the performance of the app through effectively training the deep learning system.

(2) Clinicians: Because many parents will use the app to screen their children at home, clinicians' role in large-scale preschool vision screening will be lessened. However, the app will also contribute to revealing more previously undetected visual impairment. Therefore, clinicians may need to shift their focus to improving the accuracy of comprehensive detection of specific eye diseases instead of identifying general abnormalities in the eyes.

(3) Researchers in the fields of AI and visual impairment: Researchers need to cooperate with app developers and users to consistently validate the app's performance. They will need to reveal the internal logic of the app to gain the trust of the general public.

(4) Businesses, organizations, and institutions providing funding: The performance and influence of the app are directly associated with their interests. While providing funds to support the app's development, they will also need to conduct validations.

(5) Government: Governments can also fund the design and development of such apps. At the same time, they can fund research to investigate the workflow and testing results. For an AI-based system that aims to provide benefits to the general public, the government has the responsibility to support and regulate it.

(6) Users: Users are direct beneficiaries of the app. They need to strictly follow the instructions while using it for vision screening and may report concerns or suggestions to promote improvements to the system.

Three ethical and strategic issues are related to these stakeholders if this kind of app is to be applied on a wide scale.

Data Privacy

First, detection using the app requires recording videos to identify abnormalities in eye movements and facial expressions. Videos of faces, however, are personal data that needs to be well-protected. The smartphone app may violate users' privacy by extracting and using this personal information for commercial purposes if not well-coordinated. Multiple scholars have recognized the presence of this phenomenon in daily life. Zuboff (2019) describes the practice of intentionally claiming "human experience as free raw material for hidden commercial practices of extraction, prediction, and sales" while customers are ignorant as "Surveillance Capitalism". If the AI system in the app remains a black box to its users, the general public could be concerned about the possibility of "Surveillance Capitalism". The app developers and businesses, organizations, and institutions behind the app could potentially use children's facial data to train algorithms for their benefit without their consent. This is an unethical way to violate human rights. Therefore, it is important for app developers

to increase the transparency of their model by directly pointing out how they store, manage, and protect user data from inappropriate external utilization.

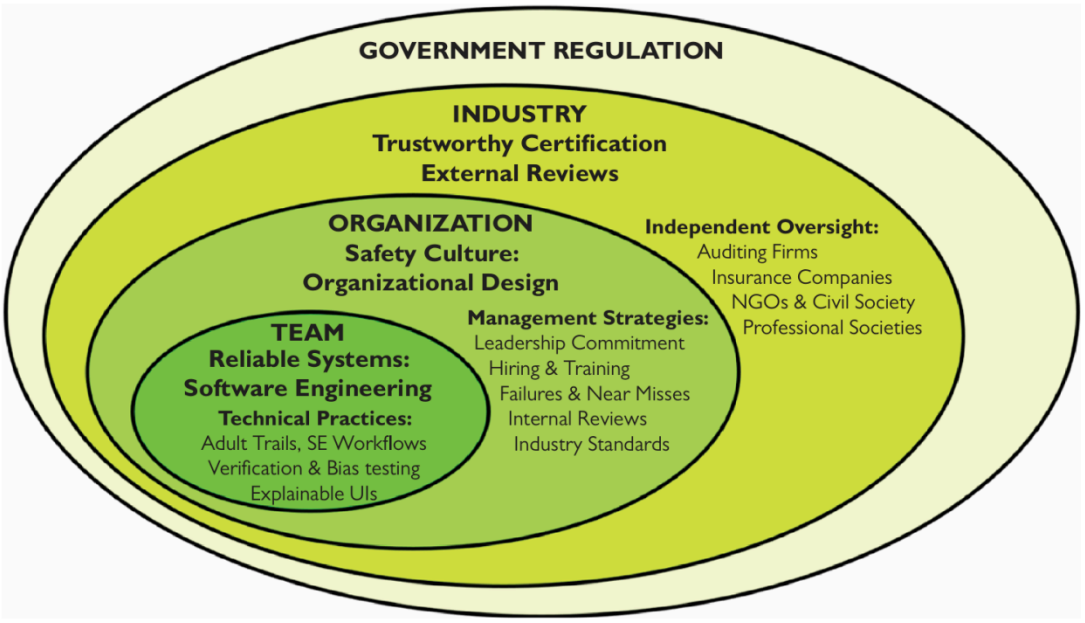
Algorithmic Bias

Another major ethical concern related to all AI systems is algorithmic biases: AI may favor certain conditions or groups of people, causing inequity. In the case of AI-based smartphone apps to detect visual impairment, such bias could be exemplified by the system being more accurate for a particular race. Previous examples have shown this possibility. Buolamwini and Gebru (2018) revealed that multiple facial analysis algorithms presented lower accuracy for people with darker skin, particularly women. However, those algorithms were adopted by security agencies to identify suspects. This bias could significantly harm Black people through discrimination, exacerbating existing racial bias and mistreatment. The proposed AI-based smartphone app also consists of facial analysis algorithms and thus can present similar biases. To prevent algorithmic biases from harming users, the app needs to be continuously tested within its range of applications, which will require governance and regulation from parties beyond app developers.

A governance structure proposed by Ben Shneiderman (2022) can be implemented to achieve the purpose of recognizing algorithmic biases, as shown in Figure 2.

Figure 2

Governance Structure for AI-based Smartphone Apps



Note: The four-level governance structure is shown as green nested ovals. From the inner to the outer layer, the ovals present: (1) Team: reliable systems on software engineering; (2) Organization: safety culture through organizational design; (3) Industry: trustworthy certification through external reviews; (4) Government regulation.

Initially, the app developers need to aim to construct a sound AI system through testing and evaluation processes. Organizations, or the technological companies behind the app developers, are responsible for encouraging app developers to achieve their goal by constructing a safety culture. That is, leaders should convey the value of equity and encourage internal reviews to validate the system. Independent industries should then conduct external reviews and oversight, further promoting the evaluation process of the app across geographic areas and populations. Subsequently, governments hold the responsibility to regulate. This is particularly important for an AI application like the visual impairment detection app because it intends to achieve general good for the public rather than making profits.

Governments can fund research teams to validate the stability of detection results across genders and races and reveal potential biases. The US Congress has already adopted

this approach, funding the US National Transportation Safety Board (NTSB) to send teams of experts to conduct field research on AI incidents (Shneiderman, 2022). This allowed the NTSB to provide insightful reports on current AI limitations and impose pressure on AI developers to reduce algorithmic biases. The FDA authorization is another example of government regulation: the FDA conducts a thorough review and evaluation of a medical AI system before authorizing it for general use among the public. If the governance structure proposed by Shneiderman is implemented in the smartphone app, the AI system will not only have limited chances of showing biases but also be trusted by the public, accelerating its progress in positively affecting more people.

Accessibility and Affordability

The third issue is accessibility and affordability: a strategic issue. Since the app is designed to provide the general public with a solution for easy visual screening, a question arises: Who is funding the development and maintenance of the system? If the smartphone app were costly for the users, it would fail to address the undercoverage issue because those with limited financial status would not be able to access the system. Therefore, businesses, organizations, industries, and governments should be responsible for funding app developers to create and continuously refine their products. In the case of AIS, social organizations, institutions, and government agencies all contribute to financial support. The apps to be made soon may take different approaches. For instance, technology companies may realize the potential of this AI solution and develop a system with similar functions, in which case, they would be responsible for the financial cost. However, with the purpose of helping national and even global communities, these smartphone apps should be fundamentally supported by governments. Even if governments do not fund them directly, it is necessary to have oversight over technology companies and developing teams to ensure that they do not transform the system into a product that prioritizes their own benefits.

Conclusion

AI-based smartphone apps have the potential to revolutionize early childhood vision screening by addressing the considerable under-coverage of current practices. As demonstrated by AIS, the apps can deliver high diagnostic accuracy and accessibility, particularly for children aged 0–5, regardless of socioeconomic background or geographic location. The design of such apps also fits the requirement of human-centered AI, thus maximizing human benefits. However, successful large-scale implementation depends on addressing three key challenges: protecting user privacy, mitigating algorithmic bias, and ensuring equitable access through proper funding. Transparent data handling, multi-stakeholder governance, and public-sector support are essential to maintaining the ethical integrity of smartphone apps. Ultimately, when designed, developed, and deployed responsibly, AI-based smartphone apps can break the cycle of preventable visual impairment and its long-term social consequences, transforming not only healthcare delivery but also the life trajectories of millions of children around the world.

Author's Note

Throughout the process of drafting this essay, I used multiple AI tools for brainstorming, idea generation, and source suggestions. For instance, I asked DeepSeek to modify my research question, providing me with ideas of questions that I want to focus on and demonstrating the varying perspectives to be considered. With the help of DeepSeek, I articulated my question: "How can AI-powered diagnostic tools improve early detection and treatment of eye diseases (amblyopia and its associated risks) in visually impaired populations?" I subsequently narrowed the targeted population to children aged 0-5 due to the discovery of their high vulnerability. ChatGPT and SciSpace were two helpful AI tools that helped me find sources. I would provide prompts such as "give me some sources on …". After the two AIs generated multiple sources with a description of each, I would select the

most relevant ones to read in detail. I've listed the three used AI sources in the **References** section.

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