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REVIEW

# Visual Prostheses in the Era of Artificial Intelligence Technology

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**Background:** Over the past few decades, technological advancements have transformed invasive visual prostheses from theoretical concepts into real-world applications. However, functional outcomes remain limited, especially in visual acuity. This review aims to summarize current developments in retinal and cortical prostheses (RCPs) and critically assess the role of artificial intelligence (AI) in advancing these systems.

**Purpose:** To describe current RCPs and provide a systematic review on image and signal processing algorithms designed for improved clinical outcomes.

**Patients and Methods:** We performed a systematic review of the literature related to AI subserving prosthetic vision, using mainly PubMed, but also, Elicit, a dedicated AI-based reference research assistant. A total of 455 studies were screened on PubMed, of which 23 were retained for inclusion. An additional 5 studies were identified and included through Elicit.

**Results:** The analysis of current RCPs highlights various limitations affecting the quality of the visual flow provided by current artificial vision. Indeed, the 28 reviewed studies on AI covered two applications for RCPs including extraction of saliency in camera captured images, and consistency between electrical stimulation and perceived phosphenes. A total of 14 out of 28 studies involved the use of artificial neural networks, of which 12 included model training. Evaluation with data from a visual prosthesis was conducted in 7 studies, including 1 that was prospectively assessed with a human RCP. Validation with empirical data from human or animal data was performed in 22 out of 28 studies. Out of these, 15 were validated using simulated prosthetic vision. Finally, out of 22 studies leveraging a mathematical model for phosphenes perception, 14 used a symmetrical oversimplified modeling.

**Conclusion:** AI algorithms show promise in optimizing prosthetic vision, particularly through enhanced image saliency extraction and stimulation strategies. However, most current studies are based on simulations. Further development and validation in real-world settings, especially through clinical testing with blind patients, are essential to assess their true effectiveness.

**Keywords:** blindness, visual impairment, vision restoration, artificial intelligence, rehabilitation

## Introduction

Blindness currently affects around 43 million people worldwide,[1] a number which is expected to increase to 115 million by 2050.[2,3] For centuries, efforts have been made to develop visual rehabilitation strategies to improve vision in visually impaired patients.[4] However, the clinical utility of such measures in real-life situations remains limited. The recent surge in technological advances has created new hope for enabling more efficient visual perception in blind people.

Historically, sensory substitution was the first strategy aiming to replace vision, via non-invasive methods to transfer visual information to the brain via an intact sensory modality, mainly touch or hearing. With sufficient training, blind individuals become able to read[5] and navigate safely in their local environment.[6] More recently, neuromodulation technologies have been tested in





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animal models,[7,8] with application of ultrasound or light for directly stimulating the visual cortex to evoke a perception of light or shapes, thereby bypassing the damaged sensory channel. By directly engaging the brain's visual processing center to produce visual experiences, neuromodulation holds clinical potential for individuals who have lost their vision due to retinal or optic nerve damage. As an alternate invasive approach, retinal and cortical prostheses (RCPs) apply electrical stimulation via an array of micro-electrodes placed in healthy regions of the retina or the visual cortex. Such punctate electrical stimulation evokes phosphenes, which are elementary units of visual perception, often perceived as spots of light in the visual field. RCPs aim to create a meaningful visual experience with accurate generation of a sufficiently large amount of phosphenes. Electrical stimulation through RCPs is performed based on visual signals from digital images captured by a camera in real time.

Various RCPs have enabled blind individuals to perform simple visual tasks.[9] However, present RCPs technology does not deliver sufficient visual acuity to navigate in the world. Notably, the number of phosphenes that can be accurately elicited is limited to just a few hundred.[10] Also, due to desensitization, it is challenging to maintain consistent phosphene patterns during prolonged neural stimulation. Still, even the simplest of visual representations can convey relevant information, much as a cartoon can communicate complex ideas with just a few lines.[11]

Already in 1985, the American neuroscientist Paul Bach-y-Rita and his team had foreseen that artificial intelligence (AI) tools, then at the earliest stage of development, might be important to enhance visual representations in blind individuals.[12] Their speculations applied to sensory substitution devices, which can deliver only a limited amount of perception units, due to limitations arising from brain plasticity mechanisms. However, this same reservation applies for current RCPs, which likewise deliver a limited number of phosphenes. AI is now emerging as a practical tool to optimize the use of the limited information bandwidth of RCPs.[13–15] Indeed, AI has already brought about remarkable advancements in machine visual processing, notably in the performance of complex tasks such as autonomous navigation and robotic vision. Such breakthroughs highlight the fitness of AI protocols to process and accurately interpret visual input.

By extracting salient information from a visual scene, translation of AI to RCP devices is bringing new opportunities for improving the quality and interpretability of phosphene maps in blind patients. By transmitting only salient information of a visual scene, RCPs promise to optimize the information conveyed by a limited amount of phosphenes, thereby improving the user's perceptual experience.

Ensuring that phosphenes are reliably generated at precise locations within the visual field presents another important challenge. Without constant spatial accuracy, phosphenes cannot create coherent and recognizable visual patterns that are of vital importance for the clinical efficacy of artificial sight. AI-driven models have shown potential for improving alignment between electrical stimulation and phosphene properties in a blind individual's visual field.

Further development of AI-based algorithms may contribute to make RCPs that deliver a more stable and vivid visual experience, potentially leading to better usability of visual prosthetics in daily life. In this review, we describe the current state of development of AI measures aiming to improve the RCPs performance, via optimization of the complex interactions between artificial systems, biological neural pathways, and perceptual processes. In the first section, we provide a comprehensive overview of current RCPs, focusing on their technological features, performance evaluations, and validation methodologies. We also assess the technological challenges associated with RCPs, in order to highlight the potential pathways for AI to improve such devices. In the second section, we review the current state of the art of AI and signal processing applied to RCPs. This review examines the opportunities that AI offers to RCPs, a domain that is still predominantly pre-clinical and highly heterogeneous, to assess its current value and future potential for improving clinical outcomes in blind individuals. We reviewed 28 studies covering two main applications: *saliency extraction* for optimizing visual signal transmitted to micro-electrode arrays (stimulation protocols), and *phosphene consistency models* that aim to align electrical stimulation protocols with visual perception in blind subjects. While cutting-edge methods like artificial neural networks offer exciting new possibilities, the lack of consensus over their efficacy for improving RCPs, highlights a significant knowledge gap that needs to be addressed.

## Retinal and Cortical Prostheses

### Retinal Prostheses

Retinal implants have been primarily developed for individuals affected by loss of photoreceptors in the outer retinal layers, but largely preserved inner retinal neurons, including bipolar and ganglion cells. In this context, retinal prostheses apply electrical stimulation via microelectrode or photovoltaic arrays to the remaining functionally intact cells of the retina (Figure 1). The

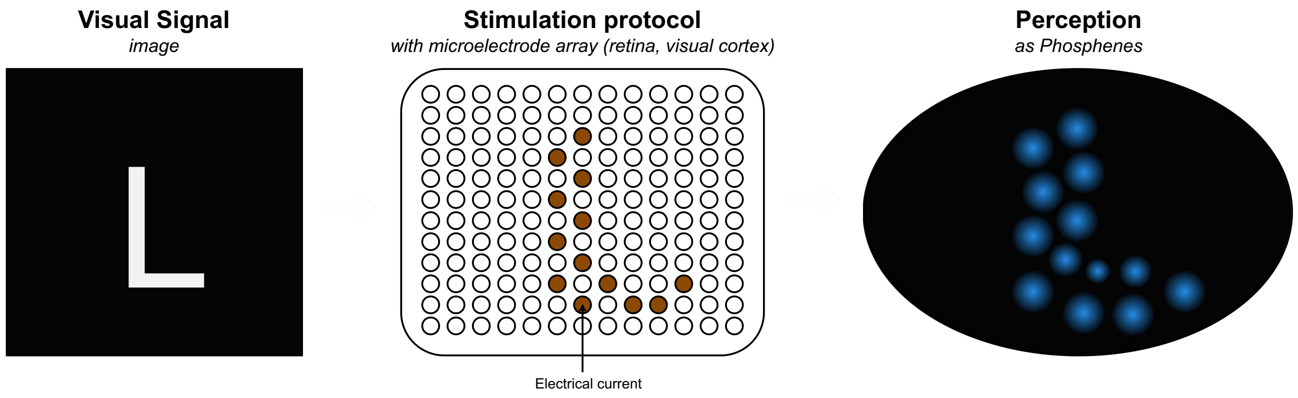


**Figure 1** Stimulation/Perception model for retinal and cortical prostheses. An input image (left) which is visible by a video camera is processed to generate an electrical stimulation via a microelectrode array (center – example with a retinal prosthesis). The electrical stimulation generates neural activity in the retinal ganglion cells, or in the visual cortex, which evokes spatially organized phosphenes, resulting in a visual percept by the blind patient (right).

prototype of this approach dates to 1956, with the implantation of a photosensitive disc into the eye of a blind patient.[16] While eliciting a few phosphenes through direct electrical stimulation of retinal cells, this approach did not provide a useful sensory experience. Renewed interest in retinal implants appeared only later during the 1990s with two parallel lines of work (Figure 2): (i) sub-retinal micro-photodiode arrays,[17] and (ii) epiretinal multielectrode arrays.[18] More recently, alternative surgical strategies-including suprachoroidal arrays that occupy the sclera-choroid plane and direct visual-cortex stimulation have further broadened the spectrum of modern RCPs presented below.

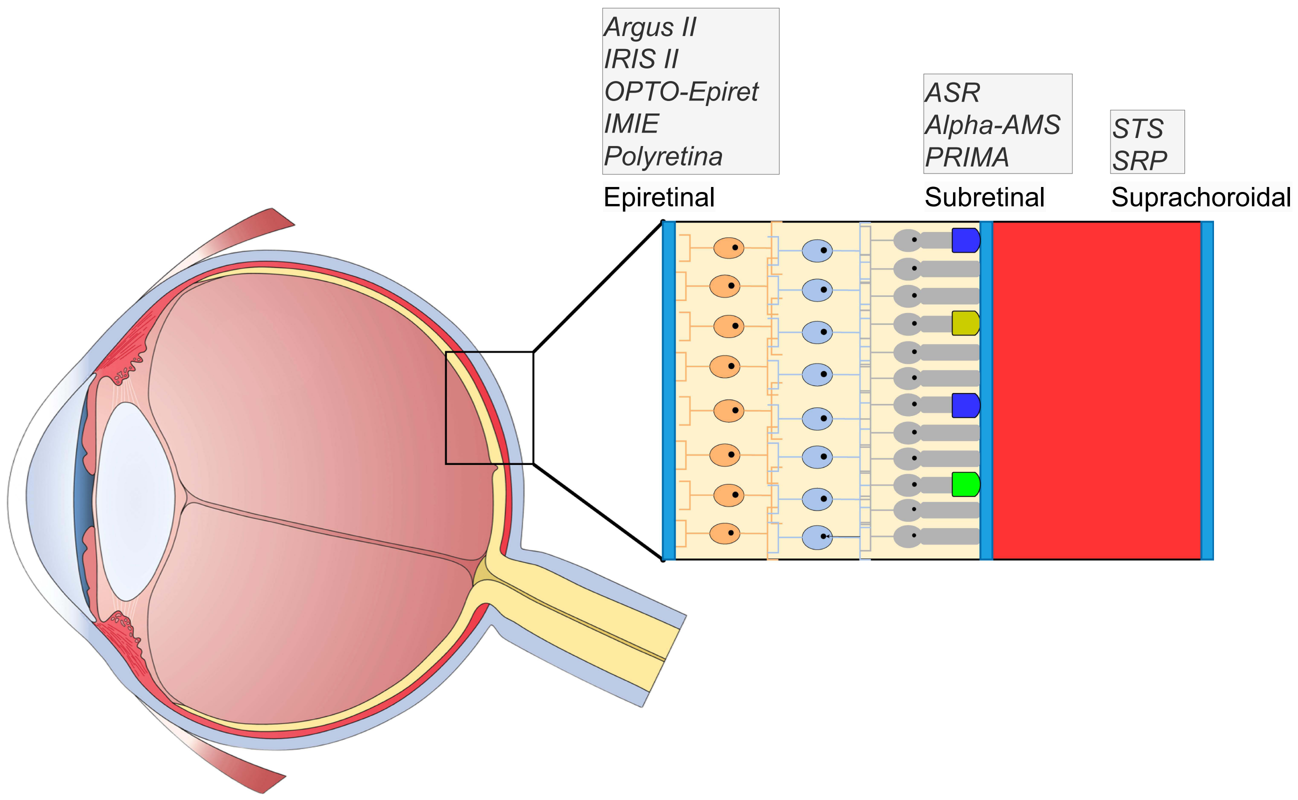


**Figure 2** Three different types of retinal prostheses have been implanted in the epiretinal, subretinal and suprachoroidal space of the human eye. All three technologies have demonstrated an ability to elicit phosphenes in late blind patients.


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As shown in Figure 1, the goal of retinal prostheses (and more generally, RCPs) is to emulate an original visual signal with a pattern of phosphenes, the original signal often being captured in real-time by a camera. However, individual phosphenes can vary in shape, size, and location among patients,[19] and their number is limited by the design of the array of stimulators. Recently, various designs of RCPs have been proposed in order to improve the quality of phosphenes while reducing the invasiveness of the implants.

## Epiretinal Prostheses

In 1998, the first cohort-based human study of a retinal prosthesis showed that electrical stimulation of the inner retinal surface elicited retinotopically appropriate phosphenes in 14 patients with end-stage retinitis pigmentosa or age-related macular degeneration, including individuals with no residual light perception.[20] In 2001, the American company "Second Sight" developed the first modern epiretinal device[18] designed for blind individuals blinded from outer retinal degenerative disease. The Argus I is a 4×4 array of 16 electrodes that is placed over the inner surface of the retina. Its successor, the Argus II,[9] used 60 electrodes, leading to demonstrably higher visual acuity[21] compared to its predecessor, Argus required surgery of approximately 3 hours, and like most retinal implants,[22–25] it relied on electrical current supply through cables. Argus II received CE marking in 2011 and FDA approval in 2013. Having been implanted in more than 300 patients, the device has undergone rigorous clinical evaluations. Unfortunately, maintenance support of the Argus II was discontinued in 2020[26] due to financial reasons.

Later, the 155 electrode IRIS II device, developed by the French company "Pixium Vision", obtained CE marking in 2016. Due to its short operating lifespan, its development was halted in favor of the subretinal prosthesis PRIMA. The 245 electrode IMIE 256 developed by IntelliMicro Medical (China) and Golden Eye Bionics (US)[23] is currently the only epiretinal prosthesis undergoing evaluation in humans.

Two new epiretinal prostheses with photo-sensitive materials are currently under development. The German-manufactured implant OPTO-Epiret contains an array of photodiodes to capture an image formed on the retina, without input from an external camera. Along the same lines, the Polyretina device developed at the École Polytechnique Fédérale de Lausanne (EPFL) delivers the greatest pixel count among retinal prostheses (10,498) and offers a wide field of view (46°).[27] So far, these devices have only been evaluated in animal models.[28,29]

## Subretinal Prostheses

Subretinal prostheses were developed as a possible solution to the poor visual acuity achieved by the epiretinal prostheses described above. Among the various models, Artificial Silicon Retina (ASR) retinal implant[30] developed by "Optobionics" (USA) was the first to receive FDA approval, in 2000. However, the increased visual acuity experience by recipients with the device ON proved to reflect a neuroprotective effect from the electrical stimulation, rather than elicitation of phosphenes,[31–33] leading the company to discontinue this project.

In 2010, "Retina Implant AG" (Germany) released the Alpha-IMS implant which has 1500 electrodes. Although results of clinical trials suggest that Apha-IMS implants can impart improvements in light and object perception, their performance as measured by the Landolt C test remains unsatisfactory.[22] The Alpha-IMS was replaced by its successor, the Alpha-AMS.[34] Although both devices obtained CE marking, they were never commercialized due to their insufficient technological and clinical performance, and the company was dissolved in 2019.

In 2017, Pixium Vision introduced the PRIMA, a prosthesis based photovoltaic pixels stimulation,[10] which was initially tested in five blind individuals.[35] Despite having fewer stimulators (378) than the Alpha-IMS, testing showed a good correlation between the number of stimulators and visual acuity, achieving a visual resolution of approximately 1.2 pixels. Also, compared with the Argus II and other RCPs, the photosensitive nature of PRIMA stimulators allowed to remove the need for cables and inductive power supply, making the device and its surgery less invasive. The PRIMA device is currently undergoing Europe-wide testing in a cohort of 38 patients in support of a CE marking application. Pixium Vision was acquired by Science Corporation in 2024 due to financial reasons.

## Suprachoroidal Prostheses

The more recent emergence of suprachoroidal prostheses (2014) holds promise to reduce the invasiveness of the requisite eye surgery.[24] By placing the implant between the firm fibrous sclera and the outer choroid, there is no need for vitrectomy. However, this approach leads to greater distance between the implant and the targeted RGCs, which may degrade performance. Two such prostheses are currently under development: the Suprachoroidal–Transretinal Stimulation (STS) prosthesis, developed by the University of Osaka, Japan,[36] and the Suprachoroidal-Transretinal Stimulation (SRP) prosthesis, developed by the Bionics Institute, Australia[25] (Figure 2). So far, the SRP has demonstrated better clinical outcomes, possibly due to the larger size of the implant, which delivers a broad view compared to other retinal prostheses. The evaluation of the clinical efficiency of suprachoroidal prostheses has so far focused on low-contrast situations and mobility tests, while their effects on visual acuity remain unreported.

## Cortical Prostheses

### History

In 1968, the first proof-of-concept was provided that focal electrical stimulation of the human visual cortex can evoke discrete phosphenes,[37] paving the way for later cortical visual-prosthesis research. In the 1970s, the Dobelle Eye,[38] consisting of 68 platinum electrodes connected to a camera, was implanted in a blind adult patient. The device remained functional for more than twenty years and, after a hardware upgrade in 2000, enabled him to perceive phosphene clouds sufficient to distinguish object outline. Since then, several other implants for stimulating the striate cortex (V1) have been evaluated (see section 2.2.3). Direct stimulation of V1 allows circumvention of the retina, thereby potentially addressing a wider range of visual diseases compared with retinal prostheses. Today, only a few blind people (all of whom were late blind) have received intracortical visual prostheses. Of note, stimulation of the visual cortex in congenitally blind individuals can inadvertently produce tactile sensations rather than visual phosphenes, particularly in blind subjects who had undertaken extensive training with sensory substitution systems.[39–41]

### Phosphene Generation

Phosphene generation in V1 relies on retinotopic mapping, which refers to a systematic spatial organization in which adjacent neurons in the visual cortex correspond to adjacent areas in the visual field. By accommodating this mapping, electrical stimulation at specific cortical sites evokes a pattern of localized phosphenes that mimic the spatial arrangement of visual input. This can enable cortical prostheses to generate structured phosphene patterns, thereby translating stimulation protocols into spatially coherent visual perceptions for the user.

### Current Cortical Prostheses

The Cortivis project started in 2001 with support from the Commission of the European Communities. Their cortical implant is based on the Utah array, which consists of 96-electrodes arranged in a 4×4 mm square, hence covering only part of the 15 cm2 V1 cortex (Normann et al, 2016). The system was first tested in a volunteer who had experienced no light perception over the preceding 16 years. The patient described the evoked phosphenes as flickering, colored, or colorless stars. Of the 96 electrodes, 88 reliably evoked phosphenes, with little change in their location over a 6-month evaluation period.[42]

The Gennaris project (Monash Vision's Group, Australia, 2010)[43] aimed to develop a wireless multiple-tile implant, each containing 43 electrodes, with broad coverage of the visual cortex. Initial animal tests indicated a good safety profile,[44] encouraging the group to apply for funding to perform a clinical trial with a 73 electrodes device.

The Orion prosthesis, designed by Vivani Medical (formerly known as Second Sight), is a successor of the epiretinal prosthesis Argus II. The Orion contains 60 electrodes forming a subdural array to be positioned on the medial occipital lobe. Ongoing studies aim to correlate and ensure consistency between its 60-electrode stimulation patterns and phosphenes in blind individuals[36,37.] In 2019, six blind patients were enrolled in a 6-year longitudinal study. At the first follow-up conducted two years after surgery, five patients were able to locate a white square on a dark computer screen significantly better than by chance. In the meantime, three of the six patients have had their device explanted "for various reasons unrelated to device safety or reliability", according to the 5-year feasibility study report.

Most recently, the Intracortical Visual Prosthesis project (ICVP)[45] was developed at the Illinois Institute of Technology. A single individual who received the implant in 2022 in an FDA-approved Phase I clinical trial is still wearing the prosthesis. The wireless 400-electrode device required a surgery of 4 hours and generated phosphenes allowing a LogMAR acuity of 2.33.[46] Preliminary studies with the device showed recipients to have good ability to map phosphenes in the visual field with electrical stimulation pattern and to perform simple visual tasks.[47–49]

Despite these developments, there are no commercially available RCP devices to date. Various clinical trials have been limited to small cohorts, providing heterogenous clinical outcomes (Table 1). Important challenges that remain to be addressed include safety and evaluation protocols, biological and technological limitations, as well as financial costs.

## Methodological, Clinical, and Technological Challenges Associated with RCPs

### Safety

Serious adverse events (SAEs) occurred in more than 25% of patients with Argus II, Alpha-AMS, and IMIE retinal prostheses (Table 1). The most common SAEs were conjunctival erosion and retinal detachment, with some patients needing revision surgery. Regarding SAEs with cortical implants, one recipient in the Orion trial experienced a seizure, but there is little information about the safety of other cortical devices undergoing trials. Still, long-term effects of electrical stimulation on brain tissue (few μA) and potential long-term toxicity of degraded electrodes need to be assessed.

### Evaluation Biases

There is no consensus on how to measure the clinical efficacy of RCP devices. Visual acuity tests offer a standardized way of measuring the patient's perceptual abilities, but they may be biased due to the pre-processing algorithms applied to camera images. Information on the algorithms used to transform the images into an electrical stimulation protocol is thus crucial for interpretation of visual acuity measurements. The use of high contrast (black and white) images tends to inflate results of visual acuity and reading tests, but optimization of prosthesis for such tasks may limit their usability for mobility in low-contrast situations. However, there is scant public documentation of image processing algorithms being used in current studies.

Visual acuity is most often assessed by conventional tests such as the Landolt C optotypes.[9,10,22,24] By this metric, comparison of visual acuity with the device switched ON and OFF showed improvement only for the PRIMA[35] and Argus II[9] devices. In comparison, studies on suprachoroidal devices[25,36] have generally assessed patient autonomy,

**Table 1** Comparison of Different Retinal Prostheses

| | PRIMA | Argus II | Alpha-AMS | STS | SRP | IMIE |
|---|---|---|---|---|---|---|
| Type | Sub. | Epi. | Sub. | Supra. | Supra. | Epi. |
| Clinical Target | GA | RP | RP | RP | RP | RP |
| Electrodes | 378 | 60 | 1600 | 49 | 49 | 256 |
| Array size (mm) | 2×2 | 5×3 | 4×3.2 | 5.8×6.3 | 10×7.5 | 4.75×6.5 |
| Surgery Time (h) | 2 | 3 | 4 | 2 | 4 | 3 |
| Diagonal Visual Field | 25° | 22° | <15° | 30° | 47° | 25° |
| Image Freq. (Hz) | 30 | 3-60 | 0.5-500 | 20 | NA | NA |
| Prop. SAE | 0% | 26% | 27% | 0% | 0% | 32% |
| Cohort size | 5 | 28 | 15 | 3 | 4 | 31 |
| Evaluation | VA | VT/VA | VT/VA | VT/MT | VT/MT | VT/VA |
| LogMAR OFF | 1.86 | >2.9 | NA | NA | NA | NA |
| LogMAR ON | 1.21 | 2.2 | >0.96, <2.48 | NA | NA | <1.6 |

**Notes**: The main retinal prostheses and their features, including their anatomical localization, the targeted condition, their performance, methods of evaluation.

**Abbreviations**: Sub, subretinal, Epi, epiretinal, Supra, suprachoroidal, GA, geographic atrophy, RP, retinitis pigmentosa, Prop. SAE, proportion of serious adverse events, VA, visual acuity, VT, visual tasks, MT, mobility tasks.

mobility, and object discrimination, rather than visual acuity. We indeed see a need for a more standardized approach to assess the clinical efficacy of RCPs.[50–54]

## Personalization

There is currently no consensus on the optimal temporal dynamics to be used for electrical stimulation of the retina. Some studies have proposed adapting stimulation rates[9,21] or electrical stimulation intensity[25,36] to individual cases. For cortical prostheses, adaptation of the current amplitude and frequency is also crucial to optimize brain stimulation.[55,56]

## Understanding the Phosphenes

From a neurobiological point of view, the link between electrical stimulation and perception of phosphenes is still not well understood. In the case of retinal prostheses, there is no straightforward spatial correspondence between the retinal position of electrode stimulation and the perceived location of the evoked phosphene in visual space, since stimulation current propagates across ganglion axon pathways,[57] often causing phosphenes to be elongated. In the case of cortical prostheses, phosphene location depends on numerous factors, including the individual's specific retinotopic maps and displacement or degradation of the cortical implant over time.[58] Gaze orientation also plays an important role in both phosphenes location[59] and interpretability for mobility and visual tasks.[60] These and certain unexplained variability factors represent a significant bottleneck for optimal stimulation with cortical prostheses. Machine Learning and AI approaches may help to improve the correspondence between neural stimulation and phosphene production, leading to better consistency in future RCPs (see section 3).

## Technological Challenges

We note some key limitations arising from present technologies. Research using simulated prosthetic vision suggests that obtaining a wide field of view (FOV) is important for both mobility and object recognition tasks.[61–64] However, the mean FOV of the latest generation of retinal prostheses is only 28 degrees, as compared to 135 degrees horizontal and over 180 degrees vertical for the human eye. However, measures to increase the prosthetic FOV would require larger microelectrode arrays, raising safety concerns. On the other hand, improving resolution with a fixed array size would require miniaturization of the electrodes, bringing a risk of interactions among adjoining contacts and heating. Indeed, current retinal prostheses do not combine wide FOV with high electrode density (Table 1). The Argus II and PRIMA devices were designed to reduce FOV even further, thereby providing improved image resolution through a digital zoom.[9,10,65] For cortical implants, it remains a challenge to increase the amount and coverage of phosphenes in the visual field. For example, the Utah array used by most prostheses covers only a small part of the V1 cortical surface, as noted above. This limitation might be addressed by implanting multiple arrays for better coverage. In a primate study, 16 Utah arrays (1024 electrodes) were implanted,[66] allowing the animals to discriminate letters. Still, currently available electrode arrays are rigid, and therefore unfit for stimulating human visual cortical areas involved in extra-foveal vision, which lie buried deeper in the calcarine sulcus. For this purpose, research in new large-scale surface neural interfaces for vision restoration aims at improving durability, scalability, density and mechanical compliance of brain stimulation units.[67] Recently, the use of flexible electrodes instead of a rigid array[68] has been proposed to cover a bigger surface of the visual field compared with surface Utah arrays. This approach is under development by companies such as Neuralink, Phosphoenix or Revision Implant.

## Financial and Ethical Challenges

Finally, we note that the high economic costs involved in RCP development have slowed the pace of technological progress, especially for retinal prostheses. The failure to demonstrate long-term and clinically meaningful benefits has led companies supporting the three currently most studied retinal prostheses (Alpha-AMS, Argus II, PRIMA) to cease or redirect their activity in RCP research and development. Also, lingering ethical questions need to be addressed regarding patient advocacy, prosthesis maintenance, and potential applications of visual prostheses for other purposes than vision restoration.

## Systematic Review on the Use of AI for RCPs

RCPs similarly rely on electrical stimulation to induce localized phosphenes, but the acuity and interpretability of the resulting visual image is limited by the small number of electrodes of current RCPs. The interpretability of low-resolution vision could be enhanced through information extraction, while at the same time reducing the recipient's cognitive load. This can be achieved using signal processing methods that have demonstrated efficient automated information extraction from visual signals.[69] Indeed, applying AI to optimize the highly constrained visual information flow conveyed to the blind might provide valuable benefits for the user. Figure 3 illustrates the computer-assisted optimization pipeline of visual flow for RCPs. Visual flow (phosphenes) optimization can be achieved by adjusting the electrical stimulation protocol, which is constructed from a digitally captured image. This approach was first considered in the early 2000s by various researchers after the clinical trials of Argus II. Nowadays, several conceptors of RCPs (Polyretina, Gennaris, Cortivis) have been suggesting that AI may play a crucial role in the development of RCP.[13–15,70] The Russian company Sensor-Tech has announced development of a future cortical implant, ELVIS-C, based on AI for image processing. Also, the Cortivis team developed Neurolight,[71] a platform for efficient interfacing of cortical visual prostheses with deep learning models.

We have performed a systematic review of the literature to identify algorithms which use machine learning, AI, or image processing methods for optimizing stimulation protocols. The research query used was as follows: (retinal prostheses OR prosthetic vision OR retinal implant OR cortical prosthesis OR retinal implants OR bionic eye) AND (deep learning OR neural networks OR machine learning OR computer vision OR image processing OR optimization) and covered all studies within PubMed database. A total of 455 titles and abstracts were reviewed by one author (IS) using predefined inclusion criteria: (i) application to retinal or cortical prosthetic systems for artificial vision, (ii) application of a signal-processing, computer-vision or machine/deep learning technique intended to improve RCPs. Articles not published in English, conference abstracts without full papers and editorials were excluded. In the end, 23 studies from PubMed that met all criteria and were included for detailed analysis. Additionally, 5 papers meeting the same criteria were identified with Elicit, an AI-based research tool for scientific papers, leading to a total amount of 28 studies (Supplementary Figure 1). The literature search was last updated in January 2025.

For each of the 28 papers, one author (IS) extracted a set of information for comparison. We noted the publication year and purpose of the studies, which AI techniques it relied on, if parameter tuning was performed, assumptions made on the appearance of a phosphene, and how the method was tested – numerically, in a simulator, on head-mounted gear, or with an actual implant. Whenever human subjects were involved, we added the kind of task they

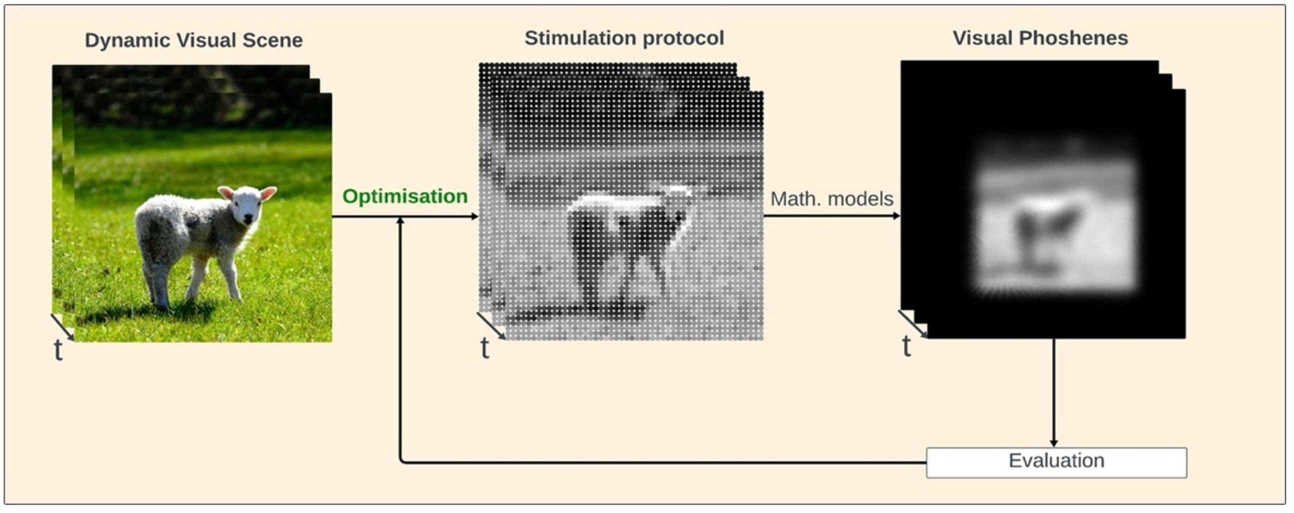


**Figure 3** Optimization pipeline for visual stimulation protocols. Artificial intelligence optimizes the transformation of a dynamic scene (left) into an electrical stimulation protocol delivered to an array of stimulators (middle), resulting in visual phosphenes (right) that emphasize the essential visual information and allows accurate phosphene mapping. This figure models the process using a 2500-electrode epiretinal implant, with a ganglion axon pathways model for visual phosphene computation.[57]

performed (eg, navigation, object recognition). Finally, we flagged studies that handled moving or dynamic scenes and wrote down the electrode count they used. The exact definitions of each field are given in Supplementary Table 1, and the full study-by-study breakdown appears in Table 2 and Supplementary Table 2.

**Table 2** Summary of Reviewed Studies on Retinal and Cortical Prostheses

| Ref | Year | Purpose | Tools | Val. Setting | Symmetric Phosphene Modelling |
|---|---|---|---|---|---|
| [72] | 2008 | Saliency extraction | CV | SPV | Yes |
| [73] | 2013 | Saliency extraction | CV | HM SPV | Yes |
| [74] | 2014 | Saliency Extraction | CV | HM SPV | Yes |
| [75] | 2014 | Saliency Extraction | CV | SPV | No |
| [76] | 2015 | Saliency Extraction | CV | HM SPV | Yes |
| [77] | 2016 | Saliency Extraction | CV | PV | No |
| [78] | 2017 | Saliency Extraction | CV | NO | Yes |
| [79] | 2017 | Saliency Extraction | CV | SPV | Yes |
| [80] | 2018 | Saliency Extraction | CV | SPV | Yes |
| [81] | 2020 | Saliency Extraction | CV | SPV | Yes |
| [82] | 2020 | Saliency Extraction | CNN | SPV | Yes |
| [83] | 2021 | Saliency Extraction | CNN | SPV | No |
| [84] | 2022 | Saliency Extraction | CNN | HM SPV | Yes |
| [85] | 2022 | Saliency Extraction | CV | HM SPV | Yes |
| [86] | 2022 | Saliency Extraction | CNN | SPV | No |
| [87] | 2019 | Saliency Extraction | CNN | None | Yes |
| [88] | 2022 | Saliency Extraction | CNN | None | Yes |
| [89] | 2022 | Saliency Extraction | CNN | None | Yes |
| [90] | 2022 | Saliency Extraction | TF | None | None |
| [91] | 2023 | Saliency Extraction | CNN | None | No |
| [92] | 2013 | SP Optimization | CV | SPV | No |
| [93] | 2016 | SP Optimization | ML | Ex-vivo | / |
| [94] | 2021 | SP Optimization | CNN, ML | In vitro PV | / |
| [95] | 2023 | SP Optimization | ML | RSPV data | / |
| [96] | 2023 | SP Optimization | NN, ML | RSPV data | No |
| [97] | 2024 | SP Optimization | NN, ML | Ex-vivo | No |
| [98] | 2024 | SP Optimization | NN, ML | Ex-vivo | / |
| [99] | 2025 | SP Optimization | NN, ML | SPV | No |

**Note**: The table includes studies year and purpose, tools used (traditional computer vision – CV, convolutional neural networks; CNN, transformers; TF, machine Learning; ML, fully connected neural networks - NN), validation setting ([head mounted] simulated prosthetic vision; [HM] SPV, retrospective prosthetic vision data; RSPV data, Ex-vivo, prosthetic vision; PV), and the use of a symmetrical phosphene model (Yes, No, None or non-applicable - /).

This systematic review identified two applications of numerical optimization methods to the task of prosthetic vision. One involved the extraction of the relevant information to be highlighted and focuses on the transformation of images into stimulation protocols (Figure 2). In other terms, studies tried to answer the question "What visual image should we deliver with a limited number of phosphenes?" which can be translated into the technical task "What is the best image transformation to be applied on camera-captured images for preserving important visual information with a limited number of phosphenes?" As highlighted in Section 2, RCPs provide a limited finite number of phosphenes in the FOV, while natural sight conveys many orders of magnitude of greater detail. To overcome this bottleneck, this first approach employed AI to enhance the original image and extract only the most relevant information through a limited number of phosphenes. The task employed two different methods, one for extracting specific features from the image such as depth information (Feature Engineering), and the other employing end-to-end AI-based optimization to find the best stimulation protocol for a given task (Figure 4).

The second application of numerical optimization of the stimulation protocol aimed to induce consistent visual patterns. It thereby answers the question "How can we consistently elicit a set of phosphenes representing the visual signal that needs to be sent to the device user?" which can be translated in the technical task "How to optimize stimulation parameters to consistently deliver phosphenes at a given location?" As highlighted in Section 2, maintaining consistency between the phosphenes that we need to provoke and the actual overlay of perceived phosphenes is a challenging task, but AI-based algorithms may provide better control over the images perceived by patients via optimization of the stimulation protocols. This procedure includes finding correspondences between electrodes and phosphene locations but also calls for personalized optimization of the stimulation parameters, ie, signal frequency and current.

We consider these two applications to be mutually complementary. Suppose that our intention is to transmit the image of a familiar person approaching the user of a visual prosthesis, as captured by its integrated camera. In the first application, AI can highlight the important information (eg, the nature of the perceived object, a person, its contours, distance, and emotional expressions) to predict the best phosphene representation of this image. In the second application, another algorithm can be

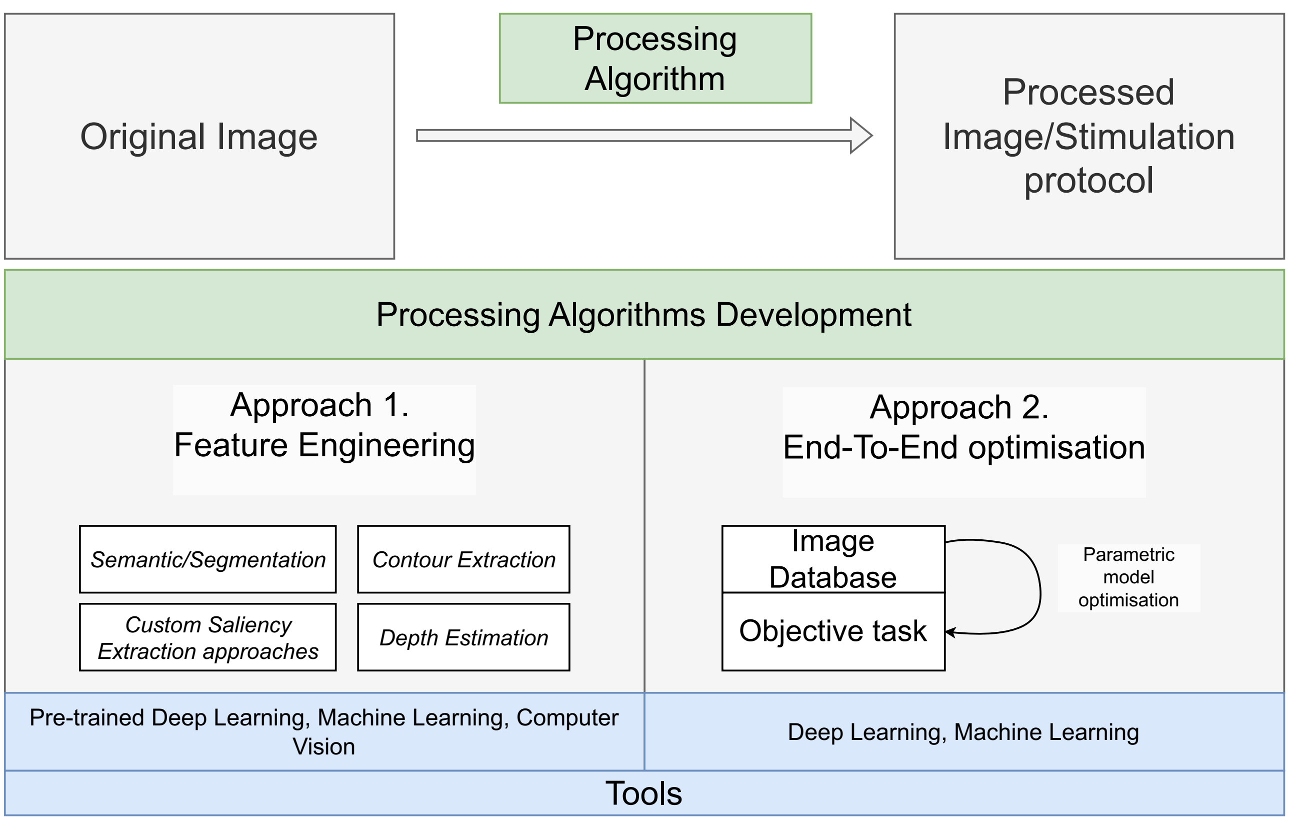


**Figure 4** Feature engineering and end-to-end approaches for saliency extraction from natural images.

used to ensure that the desired phosphene map is consistent with the perceived phosphenes. Indeed, AI methods can enhance visual perception by converting images into discernible, salient, and consistent phosphene activations. For supporting such purposes, the reviewed studies proposed using various tools, extending from traditional image processing to artificial neural networks, and using various validation settings (Table 2).

## Saliency Extraction

Direct mapping of visual scenes is not always the best approach to convey visual information,[83] since transformed views of the scene may better highlight salient visual details. Indeed, an automatic image processing method can be used to obtain a good low-resolution image, otherwise known as saliency maps. Various features have been proposed to build saliency maps for RCPs, including objects, contrasts, edges, or depth information of an image. We refer to these methods as *feature engineering*, as the methodological work involves identifying the best features for supporting the visual task. Another approach involves developing a model to optimize directly the saliency map from an input image. Here, rather than computing known features, the model is trained to find the most salient features automatically, in an approach designated as *End-to-End*. Such strategies use artificial neural networks to transform a natural image into a stimulation protocol. The method design must result in an encoding scheme that favors the extraction of salient features and may also encompass optimization of the visual flow by considering models for perception of phosphenes. Compared with feature-engineering studies, the end-to-end approaches we reviewed rely on deep-learning models that translate images directly into electrical-stimulation protocols. By embedding phosphene models within the optimization loop, they offer a more comprehensive theoretical framework. This strategy enables the simultaneous optimization of the visual features extracted from an image and the stimulation pattern that evokes those features as phosphenes. However, as detailed in Sections 3.1.2 and 3.1.3, the effectiveness of end-to-end approaches is constrained by uncertainties about phosphene-model realism and the absence of thorough validation in human subjects. These two approaches are depicted schematically in Figure 4.

### Feature Engineering

The first saliency extraction approach encountered in our review proposes constructing saliency maps by aggregating various visual features (distance, contrast, object size).[72] The authors proposed an adaptive design by applying weights on each feature depending on the scene context. For example, contrast information should be prioritized in a situation where several small objects are arranged on a work desk. The validation of phosphene maps was performed in normally sighted individuals, who were presented with saliency-enhanced phosphene maps computed from the original images. This approach to validation is known as simulated prosthetic vision (SPV). The quality of the saliency maps was evaluated by asking the participants to assess their preference for the advanced or a more basic approach, with phosphenes being modelled as simple image pixels. In an alternate approach, adaptive depth-contrast enhancement was proposed for improving obstacle detection in the path of a moving person,[76] with validation of the saliency maps through performance of visual or mobility tasks. In this study, phosphenes were not modeled as pixels but as sparse dots distributed according to a Gaussian distribution. Some phosphenes were removed (dropout) from the image to simulate malfunctioning electrodes.

More recent approaches have used convolutional neural networks (CNNs) for saliency extraction. Relevant features include object and structural edge recognition in indoor rooms[82] or clip-art style images conveying simplified representations of objects.[86] Among the 14-feature engineering-based studies identified in our literature search, the most common feature type used for saliency map extraction was image contours, which provide salient spatial information about the environment. Other features included contrast information,[73,76] semantic information,[80,82,83] depth information,[76,79,81] surface normal,[84] convolutional filters,[73,75,77] and the use of clip-art style images.[85,86]

Only one out of the 15 feature engineering studies has been implemented in human real prosthetic vision settings[77] with a suprachoroidal device. In this study, authors showed that the use of Lanczos filtering improved mean light localization success rate from 57% to 77% in 3 subjects compared with minimal visual processing. This study highlights the potential of computer vision for enhancing RCPs but was limited to basic signal processing techniques and visual tasks. Additionally, 4 of the 15 studies used artificial neural networks but were validated with simulated prosthetic vision

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only. The use of pre-trained convolutional neural networks was proposed in three studies[82–84] as a pre-processing step for saliency extraction. The models had been pre-trained on natural image datasets. These three studies have proposed to combine outputs of two deep learning models to build their saliency maps (saliency with depth,[83] contours with surface normals,[84] contours with semantic masks).[82] Only one study performed model training[86] with generative adversarial networks for image simplification. In contrast, most end-to-end approaches have leveraged specific training in their methodologies.

## End-to-End Methods

We now consider the proposition that *whatever enables a machine to solve a problem may enable humans to solve it*. This hypothesis is assumed by end-to-end optimization methods for RCPs. Instead of using models that directly extract the desired information (objects, contrast, contours), end-to-end AI approaches have been proposed to allow the model to extract the information that is judged to be necessary for performing a given visual task. In this setting, the phosphene representation of an image is learned in an indirect fashion, by instructing the model to perform a particular task. According to our proposition above, we assume that if the machine can perform a given task from a phosphene map, then this phosphene map is suitable for use by humans. Of the five end-to-end studies that we identified, two relied on auto-encoding strategies,[88,91] where the task to be learnt is reconstructing an original image, and three entailed reinforcement learning approaches,[87,89,90] for which the scope of learned tasks is wider.

Auto-encoding strategies aim to retrieve information that is lost during the image-to-phosphenes transformation. Video camera images are first transformed into a stimulation protocol, whereupon a deep neural network learns to reconstruct the original image from the low-resolution stimulation protocol. By design, the stimulation protocol usually has low-resolution to match the poor resolution of typical RCPs, such as 32×32 pixels.[88] Before reconstruction, a differentiable phosphene shape model is applied to optimize phosphene maps based on simulated prosthetic vision, rather than on the stimulation protocols. However, very few studies have proposed dynamic auto-encoding of visual inputs, and then only in the context of reinforcement learning approaches.

In deep reinforcement learning approaches, a visual task is performed within a virtual environment by a virtual agent. The deep neural network learns to extract a constrained, low-quality visual representation of its environment that allows the agent to perform the assigned visual task. Such an approach can produce saliency maps highlighting the visual information that is required for performing a visual task. This kind of AI learning is often performed in virtual environments due to the lack of real data, but current methods have employed virtual platforms with low realism, limiting their real-world usability.[87,89,90]

End-to-end approaches may offer scalable pipelines for stimulation protocol optimization, as they may encode visual stimuli in a way that optimizes its use for various visual tasks and leverage large datasets for this purpose. However, all 5 end-to-end studies were validated in a fully numerical way (Supplementary Table 3). In comparison, most feature engineering studies (14 out of 15) involved human experiments for methodological validation. Also, from a computational perspective, feature engineering approaches relied mostly on traditional computer vision methods (11 out of 14) whereas end-to-end approaches leveraged more advanced AI architectures (such as transformers)[100] or frameworks (such as reinforcement learning). Still, our review suggests that they have not yet demonstrated their effectiveness for visual tasks, as they lack validation in both simulated and real prosthetic vision settings.

## Phosphenes Modelling

The nature of phosphene perception is a crucial aspect of prosthetic vision. The objective of delivering an enhanced image to a blind person via an implant requires being able to provoke phosphenes in a consistent manner over time, and at the same desired retinal or cortical locations. Accomplishing this task requires a neurobiological understanding of the retina and visual cortex. However, without perfect understanding of these neurobiological mechanisms and with very limited control on neural activity, scientists must find the best stimulation strategy and identify the best parameters influencing phosphene shape, visual field location, and brightness.

Phosphene modeling approaches span a spectrum from idealized, symmetrical abstractions (eg, pixel-based or circular-Gaussian phosphenes) to more realistic, data-driven models incorporating patient-specific or experimentally derived phosphene shapes. Among the 28 studies reviewed, 22 employed an explicit mathematical model of phosphene perception. Of these, 14 relied on highly simplified representations using symmetrical phosphenes. Specifically, three studies relied on a pixel model, which is a one-to-one distortion-free rectangular mapping between the electrode array and perceived phosphenes. The remaining 11 studies used circular symmetric models including mainly circular dots and gaussians for representing phosphenes. However, empirical data show that phosphenes are not symmetric, either for retinal[101] or cortical[42] implants. Using perfectly round, pixel-like or symmetrical phosphenes in silico inflates apparent performance: edge-detection or object-recognition algorithms that look excellent on a tidy 10×10 grid often break down when the same stimulation elicits skewed "comet" shapes in vivo. Such models also mask safety constraints, because real elongated phosphenes imply wider current spread and higher charge density on axonal bundles than the simulator predicts. Finally, they may also misguide hardware design, leading engineers to prioritize electrode counts over placement accuracy, and they hinder closed-loop calibration by giving the learning algorithm a training target the patient can never actually see. In short, over-idealized phosphenes risk both overpromising clinical benefit and under-engineering robustness.

On the other hand, fewer studies (8 out of 22) used an asymmetric model, including two with a prior phosphene dictionary, one with asymmetric gaussians, and five with an axon map model (Supplementary Table 2). Based on axon mapping of the retina,[102] the axon map model was also proposed to simulate more realistic phosphene maps resulting from retinal stimulation. This model assumes that electrical stimulation of RGCs propagates through adjacent axon fibers, thus resulting in elongated shapes, and was empirically validated.[101] Finally, 5 studies did not use prior on phosphene shapes, and these were conducted with empirically measured data.

Regarding the simulation of phosphenes by cortical implants, two models were recently proposed which accounted for retinotopic mapping of V1 and the temporal dynamics associated with prolonged cortical stimulation.[103,104] The Polyretina team also conducted experiments within virtual reality to assess perception under simulated epiretinal prosthetic vision.[64] Such digital twins may help in the future for elaborating new optimization algorithms for RCPs.

## Studies on Phosphenes Perception Optimization

Even with state-of-the-art phosphene modeling, prediction of shapes, location, and brightness of phosphenes remains challenging due to intra-patient variability in neural responses arising from cortical stimulation. Indeed, optimization of stimulation input parameters is also a critical factor after device implantation. To address this issue and improve consistency between the desired visual signal and the perceived phosphenes, various approaches have been proposed so far using machine learning of AI.

To address the phosphene shape modeling issue, three studies proposed to improve stimulation with retrospective human data obtained with RCPs. A first study used previously measured visual percepts as a dictionary to optimize image recognition and then evaluate them under simulated prosthetic vision settings using AI.[92] However, such an approach is valid only when the phosphenes can be elicited in a consistent manner, without drifting or intensity changes. Also, one study used machine learning to predict phosphene deactivation and threshold sensitivities in retrospectively collected data of Argus II users.[95]

Another approach consisted in using human-in-the-loop optimization to improve the perceived image in a simulated prosthetic vision setting.[96,99] This approach allowed inclusion of patient's preferences for stimulation parameters optimization and was proposed in two studies, one using virtual patients[96] and one using real sighted patients under SPV.[99] This approach might allow simultaneous optimization of the saliency extraction and the phosphenes consistency problem by integrating directly the patient preferences in the optimization process.

Three other approaches used empirical data from animal models to simulate the neural response elicited by RCPs. Two studies were evaluated in a mouse model involving the transduction of a calcium indicator[94] and electrophysiological measurements[93] in RGCs to provide an objective measurement of their activity. These approaches supported optimization of the stimulation parameters with neural networks and a genetic algorithm, respectively. Also, an actor model was developed to improve projection high-resolution images into smaller resolution RCP arrays.[98] High-resolution images were projected into mouse retinas with a multielectrode array that detected neural spikes from RGCs in response

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to image projection. A dataset was built and used to learn a supervised encoder improving reliability of the ex-vivo transmitted signal.

Apart from improving phosphene shapes and predicting electrode malfunctioning, AI and machine learning might also be applied to other challenging tasks in the future, including the optimization of electrodes' location or electrical stimulation patterns.

## Methodology and Validation of AI Approaches

The use of deep learning methods for RCPs was introduced only in 2017 (Figure 2), while computer vision-based models date back to a decade earlier. AI approaches focus on the optimization of electrical stimulation protocols, which are often evaluated using simulated prosthetic vision (15 studies). Simulated prosthetic vision in sighted subjects is a powerful tool for evaluating AI methods in interpreting visual phosphenes. However, the realism of these models is frequently limited by an overall neglect of phosphene models, which are often confused with electrical stimulation protocols,[72] or by using unrealistic simulation settings.[76,88] It is necessary to make a distinction between stimulation protocols (current amplitude and frequency sent to each electrode) and perceived phosphenes in the task of modelling phosphene perception.[57,102,103]

Twelve out of 28 studies leveraged parameters optimization, indicating that AI algorithms were trained in an original fashion (data or architecture). For studies released since 2019, 12 out of 18 studies involved parameters optimization, suggesting that there was an increase in efforts to train AI models specifically designed for RCPs recently. Additionally, we observe a notable rise in the use of artificial neural networks for RCPs since 2017 (Figure 5).

Also, 12 out of 28 studies have included dynamic aspects of vision, meaning that 16 out of 28 studies considered only static measurements or images in their methodology. A major challenge lies in the integration of visual scenes as a continuous flow rather than as static images. Visual representations are enabled by focusing on a few objects and having the ability to focus on details of the visual scene on demand at a given moment. Consequently, even in the context of a static visual scene, the dynamic dimension of attention mechanisms is inseparable from vision itself. It has been suggested that sighted individuals build mechanisms of internal visual representations through a tradeoff between spatial complexity and temporally increased complexity.[105] With artificial vision, the dynamics of extrapolation achieved through multiple views of the same scene may convey crucial information to blind patients.

Validation strategies for the 28 AI-driven RCP studies were highly heterogeneous, mirroring the diversity observed for conventional (non-AI) RCP work highlighted in Section 1. Eleven investigations focused on generic visual recognition (light, letter, object, or scene recognition/localization), five had tackled mobility-related challenges (navigation and obstacle avoidance), and two had relied solely on subjective preference. Only one study had included an implanted human participant, evaluating visual acuity across several image-processing pipelines. This diversity highlights that AI research in RCPs still lacks a unified goal with performance metrics, datasets, and even task definitions differing markedly. Hardware assumptions

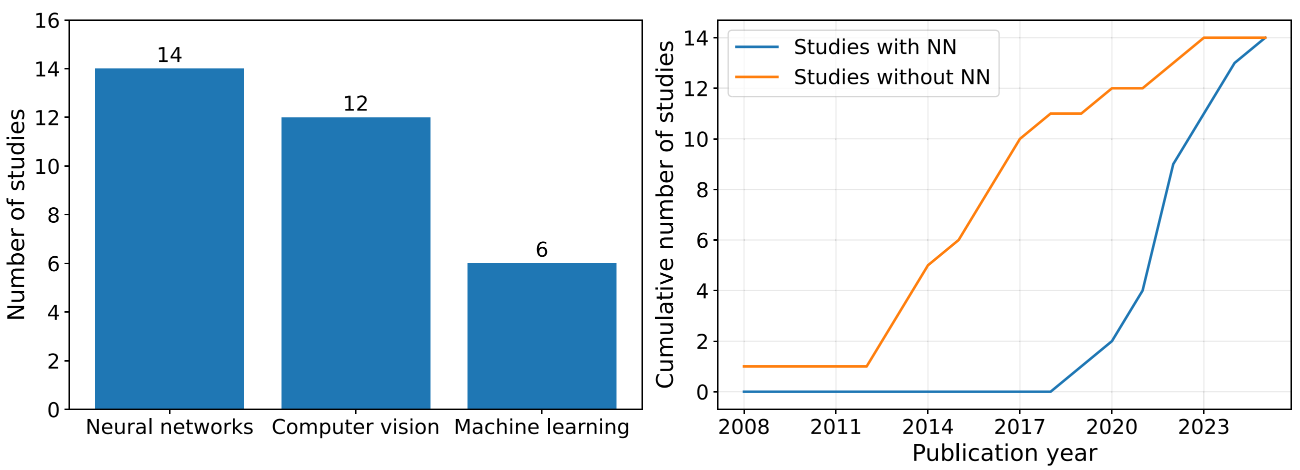


**Figure 5** (Left) Distribution of AI tools used for visual information processing in the reviewed studies. (Right) Cumulative study counts over time for the three approaches (NN – neural networks).

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varied just as widely. Electrode-array sizes ranged from 20 to 4096 channels, whereas most RCPs use fewer than a few hundred electrodes (Table 1). Such variability in both task design and array geometry blurs cross-study interpretation and hampers the emergence of a standard benchmark, making it difficult to discern whether improvements arise from algorithmic innovation, more forgiving evaluation settings, or simply denser stimulation grids.

## Discussion and Perspectives

Various efforts have been deployed to leverage AI-driven algorithms for addressing the intricate challenges of optimizing the performance of RCPs. By exploiting the ability of computational methods to analyze and adapt to complex neurobiological processes, AI holds significant potential to enhance visual stimulation protocols to elicit consistent and precisely located phosphenes. In the field of restoring vision to the blind, these emerging technologies present an innovative approach for translating intricate visual scenes into phosphene representations, with optimal delivery for conveying information that is salient for tasks such as object identification and navigation. However, at present, real-world deployment of these methods remains impeded by the tiny pool of recipients with functioning prosthetic vision and incomplete modeling of the image-to-phosphenes flow.

Our review reveals that recent deep-learning initiatives have gravitated toward simulation-based models of phosphenes, because it allows researchers to generate *virtually unlimited* stimulation-perception pairs that can be evaluated with normally sighted individuals. These synthetic corpora make it feasible to train state-of-the-art neural networks whose performance often scales with millions of samples – yet they inevitably inherit the simplifying assumptions of the simulator. Recently, the field has therefore turned its attention to biologically plausible phosphene simulators that embed stimulation to retinal–cortical transfer functions with respect to electrode mapping. If forthcoming clinical studies confirm the predictive fidelity of these models, they could transform simulation from a convenient stand-in to a *trusted proxy*, enabling both large-scale AI training and pre-emptive safety screening before first-in-human testing. The creation of a large-scale stimulation-perception datasets might also improve the fitting of phosphene models while integrating better biological safety limits.

Across all virtual-setting investigations, we found no quantitative assessment of safety limits – such as electrode current density, thermal rise, or cumulative charge – and none addressed the power draw resulting from the use of AI algorithms; this omission represents a critical barrier to deploying current in-silico algorithms in real RCP users. Also, apart from safety constraints related to electrical stimulation, other safety issues might be raised by the robustness of the AI models that drive scene analysis. Deep-learning pipelines can miss objects, misclassify hazards, or misjudge depth whenever lighting, motion, or context shifts beyond the training distribution. These mistakes risk steering users into obstacles or fostering unwarranted confidence in unsafe situations. Yet none of the reviewed studies reported systematic stress-tests, uncertainty tracking, or fallback modes to keep such errors benign. Incorporating rigorous robustness benchmarks, real-time error bounds, and automatic fail-safes must therefore precede any large-scale clinical tests.

Finally, although AI-based saliency extraction and stimulation-protocol optimization are complementary, researchers have only combined them in end-to-end pipelines whose validation has been confined to purely numerical simulations. A unified framework, validated with human data, that jointly targets the selection of task-relevant visual features and the corresponding electrical stimulation parameters, while also explicitly accounting for individual neuro-biological constraints and user preferences, could bring algorithmic goals into much closer alignment with clinical reality. Establishing such an integrative, standardized benchmark would not only harmonize the assessment of prosthetic-vision performance across laboratories, but also generate the decisive clinical evidence still needed to confirm the practical benefits that AI can deliver for users of RCPs.

## Conclusion

In summary, contemporary AI-driven research targets two persistent limitations of RCPs: the narrow visual-flow bandwidth that current hardware can transmit and the still-imperfect mapping between electrical stimulation and the phosphenes it evokes. Accordingly, the surveyed studies focused on saliency extraction from camera-captured images to be perceived through RCPs, and on transformation of the visual input in an electrical stimulation pattern so that stimulation more faithfully mirrors user perception. The convergence of improved biophysical models, patient-specific tuning strategies and advanced saliency-extraction methods offers a credible route toward clinically meaningful artificial vision.

Yet, most advances have been demonstrated only in simulated vision with just a few investigations carried out on data from animals or humans. Simulated prosthetic vision studies often relied on oversimplified phosphene models and ignored residual vision of blind implant users. As a result, we still lack convincing evidence that high in-silico performance translates into better everyday vision with RCPs. Bridging this gap will require realistic modelling on phosphene shapes and safety limits, and, above all, involvement of human recipients using RCPs. Until such resources and validation studies are in place, claims of functional benefit of AI for RCPs must be regarded as preliminary.

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DR is an advisory member of the European Society of Digital and Integrative Pathology.

DM is an advisory board member of Optomed, Finland. The authors report no other conflicts of interest in this work.

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