42 Hill-RBF: Improving IOL Power Selection by Artificial Intelligence

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The nineteenth-century American author Mark Twain once observed that change occurs at the edges and works its way in. Rather than instantly being thrust upon us, a fundamental shift in how we work gradually arises from areas outside things familiar.

In 1962, Everett Rodgers outlined how individuals are likely to adopt new technology in his book *The Diffusion of Innovations* [1]. Most are unfamiliar with this seminal work, but almost everyone knows the vocabulary originating from it.

Rodgers observed that 16% of any group presented with a new technology consists of what he refers to as "laggards" who will change what they do only if no other option is available. Another 34% consists of a "late majority" who borders on cynical and only follows established norms. Thirty-four percent are the "early majority" who will try something new only after someone else tries it first. 13.5% are "early adopters" who quickly see the value of a new idea and incorporate it. 2.5% could be termed "innovators." The adoption of new technology is never universal, regardless of how transformative it may be.

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It is a little appreciated fact that much of the technology used in ophthalmology comes to us from other areas. We all know the story of Charles Kelman. His idea of phacoemulsification for cataract surgery arose from a form of tooth-cleaning technology in the 1950s. The first American physicist to receive the Nobel Prize, Albert Michelson, developed the nineteenth-century principle of interferometry. Adolf Fercher at Carl Zeiss in Germany and Wolfgang Haigis at the University of Würzburg used this principle to measure the axial length of the human eye with a previously unknown accuracy and reproducibility [2–5].

There are many examples of ophthalmology, in general, and eye surgeons, in particular, freely borrowing technologies from other fields. The adoption of artificial intelligence for intraocular lens (IOL) power selection is no different.

Accuracy

The evolution of intraocular lens power calculation accuracy, and the technology driving it, is often one step behind the demands of each new and more sophisticated generation of intraocular lenses. For more than 40 years, ophthalmologists have been pursuing perfection, only to face a variety of obstacles at multiple levels.

A significant limitation of all vergence-based intraocular lens power selection methods is

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estimating the effective lens position (ELP), which can account for as much as 30% of the calculation accuracy [6, 7]. Even though more modern methods tend to do better than older ones, an exact plan for determining the ELP remains elusive.

The Haigis formula optimization database of more than 300,000 cases shows that most cataract surgeons have a ± 0.50 D accuracy of 78%. Only 6% of surgeons have an 84% ±0.50 D accuracy, while less than 1% of surgeons have a ± 0.50 D accuracy of 92% or better [8]. As cataract surgeons, we all are being judged by patients and peers by our refractive outcomes. There remains much room for improvement.

While traditional and more modern formulas each have benefits, it is becoming evident that IOL power selection based solely on Gaussian optics may have reached an expiration date. Given this seemingly insurmountable limitation, why not move in an entirely different direction? [9] In other words, fundamentally change the conditions of the exercise. Exploring how an artificial intelligence model might be used to solve this problem seemed to be the obvious next step in today's world of increasingly sophisticated development software.

Artificial Intelligence for IOL Power Selection

The first attempt at using artificial intelligence for IOL power selection was by the American ophthalmologist Gerald Clarke, MD, assisted by Jeannie Burmeister, RN, in 1997 [10]. The authors used a neural network and compared the accuracy of these predictions to the first version of the Holladay formula published in 1988 [11].

In this study, using conventional 10-MHz ultrasound to measure axial length, the Holladay formula had a ± 0.50 D accuracy of 38%. In comparison, the neural network had an accuracy of 62.5%. While not consistent with today's accuracy standards, the use of artificial intelligence resulted in an enormous improvement. However, such an approach did not gain traction due to rudimentary computing power, software that was challenging to set up and refine, and a tendency to overfit the data. Like many groundbreaking ideas, it was years ahead of its time. Artificial intelligence for this purpose would not be tried again in a meaningful way until more than a decade later.

The way a neural network works is by mimicking the human neuron. It has inputs similar to neuronal dendrites and a system of summation and recalculation, very much like a cell body. It transfers the output in a way similar to a neural axon. During the evaluation phase, inputs merge into a final prediction through the network containing mathematical weights. These weights are adjusted and then readjusted throughout training by repeatedly moving prediction errors through the network via a process known as backpropagation.

In 2012, a core group of ophthalmologists and Peter Maloney, an engineer working at the American company MathWorks, began to investigate IOL power selection using artificial intelligence, employing radial basis functions [12]. The original investigators included Li Wang, MD PhD, and Doug Koch, MD, both from Baylor University in Houston, Texas; Sheridan Lamb, MD, a private practitioner in Du Page, Illinois; Johnny Guyton, MD, a private practitioner in Warner-Robins, Georgia; Adi Abulafia, MD, a hospital-based ophthalmologist in Israel and Warren Hill, MD, as the project leader. Later, Jonas Haehnle, PhD, a mathematician working at Haag-Streit AG in König, Switzerland, was added. This group has since expanded to a total of 44 investigators in 22 countries.

The project's stated objective was to increase patient safety and physician confidence and reduce the many burdens associated with an unanticipated refractive outcome. The final goal was to create a self-validating IOL power selection method as simple to use as the iPhone, independent of vergence calculations and without reliance on the effective lens position [8].

Making the Most of What's Available

A significant benefit of artificial intelligence is that it can bypass some shortcomings of current measurement technologies and make the most of what's available. This approach is also well-suited to solve real-world problems where ideal models are unavailable or less accurate than desired. IOL power selection is the poster child for the lack of a perfect, real-world model.

Physical models based on Gaussian optics assume that the measurements correctly represent the physical reality, which is rarely the case. Some of these measurements have systematic biases that must be identified and, if possible, corrected. There are also varying levels of measurement uncertainty. For example, the combination of directly measured anterior and posterior keratometry for virgin eyes is generally less accurate than anterior keratometry and a theoretical mathematical model for the posterior cornea. Significant challenges also arise with measurements that use the summation of segmental axial length. The lens thickness measurement has systematic errors and a high uncertainty level due to the cataractous lens's unknown refractive index.

Physical models also need to make assumptions about certain aspects that cannot be measured. As previously mentioned, the effective lens position is an essential aspect of IOL power selection based on a Gaussian model. There are times when the physical model amplifies a given prediction error. This is more of a problem for advanced physical models than simpler ones. These ultimately must be solved using data-driven approaches.

Artificial intelligence model-based approaches avoid such errors. For example, ELP prediction errors are no longer amplified with high IOL powers. Therefore, even the first version of Hill-RBF achieved accuracies in short eyes that were better than the more traditional IOL calculations of that time.

And not least of all, purely data-driven approaches using artificial intelligence are also free of an implicit bias of the researcher. Our method learns from the data how good the measurements can be.

Developing a Real-World Artificial Intelligence Calculator

The first problem our team faced was determining which preoperative measurements we should evaluate. Initially, 13 parameters were considered, including nontraditional metrics such as the spherical aberration of the anterior cornea, pupil size, patient gender, patient age, as well as the more traditional preoperative measurements of axial length, central corneal power, anterior chamber depth, lens thickness, the IOL power implanted, the postoperative spherical equivalent, and the horizontal corneal diameter. A genetic algorithm was used to help sort this out.

Essentially, a genetic algorithm is an evolutionary, iterative factor selection process. A basic model is created, followed by multiple iterations. Subsequent iterations are then modified in a semi-random manner, creating a series of new models. During the optimization process, the best-performing candidate models are identified, retained, and then ranked. This exercise is repeated, and those factors that produce the best-performing models are identified over time.

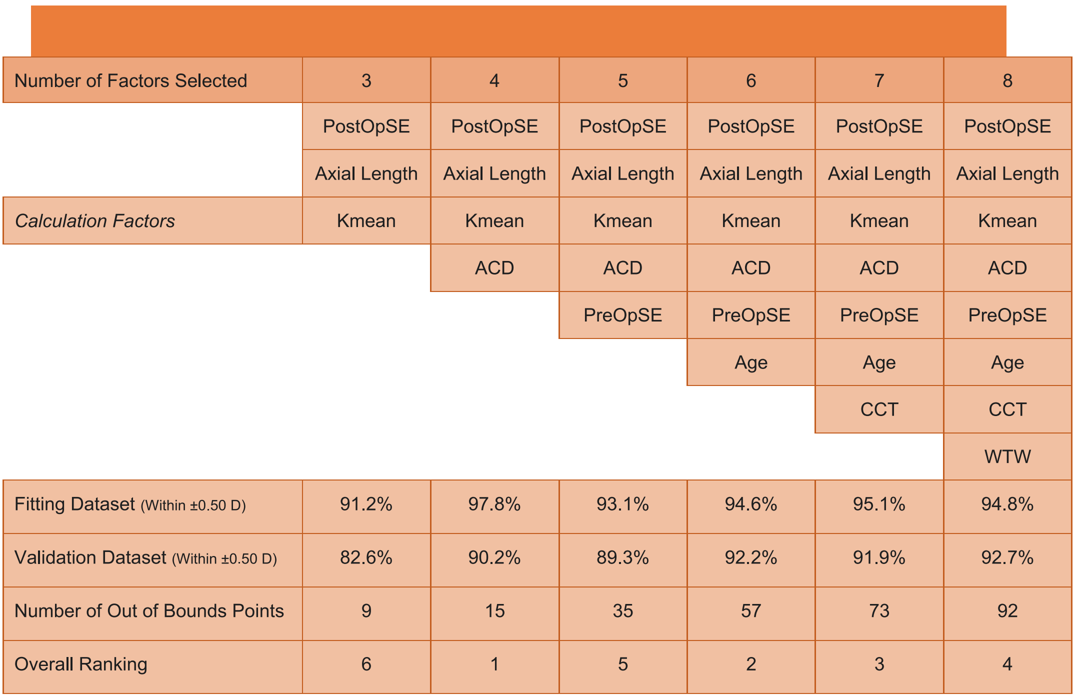
This approach has similarities to the process of natural selection as described by Darwin but would be more correctly termed artificial selection. It has been shown to outperform manual optimization methods [13–17].

The preoperative measurements resulting in the highest overall prediction accuracy were 1. axial length, 2. mean keratometry, 3. anterior chamber depth, 4. the observed postoperative spherical equivalent, and 5. the IOL power implanted.

Using 681 eyes implanted with the Alcon SN60WF intraocular lens, we fit this data to a 97.8% ±0.50 D accuracy for the artifical intelli-

Table 42.1 Genetic algorithm factor selection

Number of factors selected	3	4	5	6	7	8
	PostOpSE	PostOpSE	PostOpSE	PostOpSE	PostOpSE	PostOpSE
	Axial length	Axial length	Axial length	Axial length	Axial length	Axial length
Calculation factors	Kmean	Kmean	Kmean	Kmean	Kmean	Kmean
		ACD	ACD	ACD	ACD	ACD
			PreOpSE	PreOpSE	PreOpSE	PreOpSE
				Age	Age	Age
					CCT	CCT
						CD
Fitting dataset (within ±0.50 D)	91.2%	97.8%	93.1%	94.6%	95.1%	94.8%
Validation dataset (within ±0.50 D)	82.6%	90.2%	89.3%	92.2%	91.9%	92.7%
Number of out-of-bounds points	9	15	35	57	73	92
Overall ranking	6	1	5	2	3	4



Number of Factors Selected	3	4	5	6	7	8
	PostOpSE	PostOpSE	PostOpSE	PostOpSE	PostOpSE	PostOpSE
	Axial Length	Axial Length	Axial Length	Axial Length	Axial Length	Axial Length
Calculation Factors	Kmean	Kmean	Kmean	Kmean	Kmean	Kmean
		ACD	ACD	ACD	ACD	ACD
			PreOpSE	PreOpSE	PreOpSE	PreOpSE
				Age	Age	Age
					CCT	CCT
						WTW
Fitting Dataset (Within ±0.50 D)	91.2%	97.8%	93.1%	94.6%	95.1%	94.8%
Validation Dataset (Within ±0.50 D)	82.6%	90.2%	89.3%	92.2%	91.9%	92.7%
Number of Out of Bounds Points	9	15	35	57	73	92
Overall Ranking	6	1	5	2	3	4

Fig. 42.1 Genetic algorithm factor selection

gence model. 20% of this database had been held out for independent validation. The resulting ±0.50 D accuracy for this independent validation dataset was 90.2%. These outcomes were very encouraging, suggesting that we were on a solid footing (Table 42.1) (Fig. 42.1).

Confident in the preoperative factors selected, this data was then fit to an artificial intelligence model. For the activation function, a radial basis function was used in the hidden layer. The difference between the output layer and the fitting dataset was calculated. This process was then recalculated using a backward

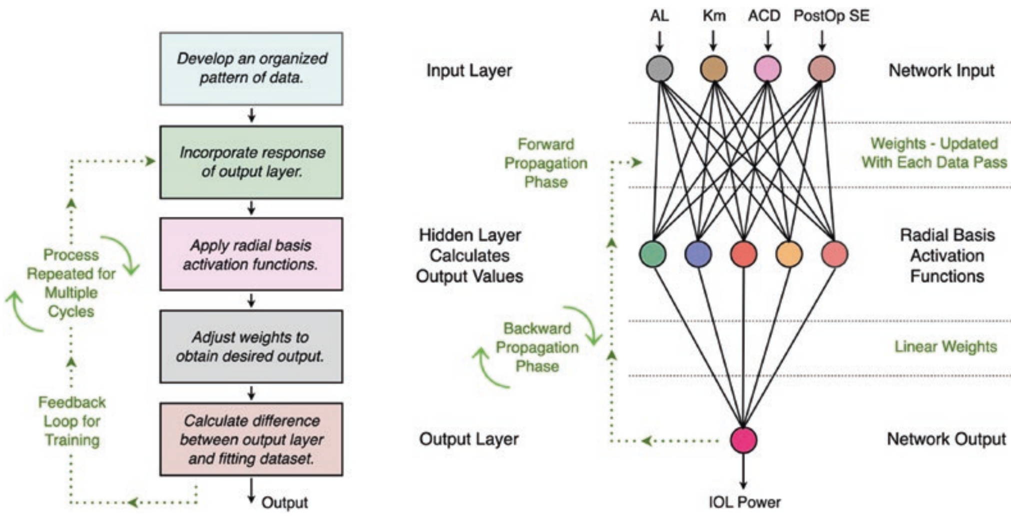


Fig. 42.2 The basic organization of a radial basis function neural network used for IOL power selection

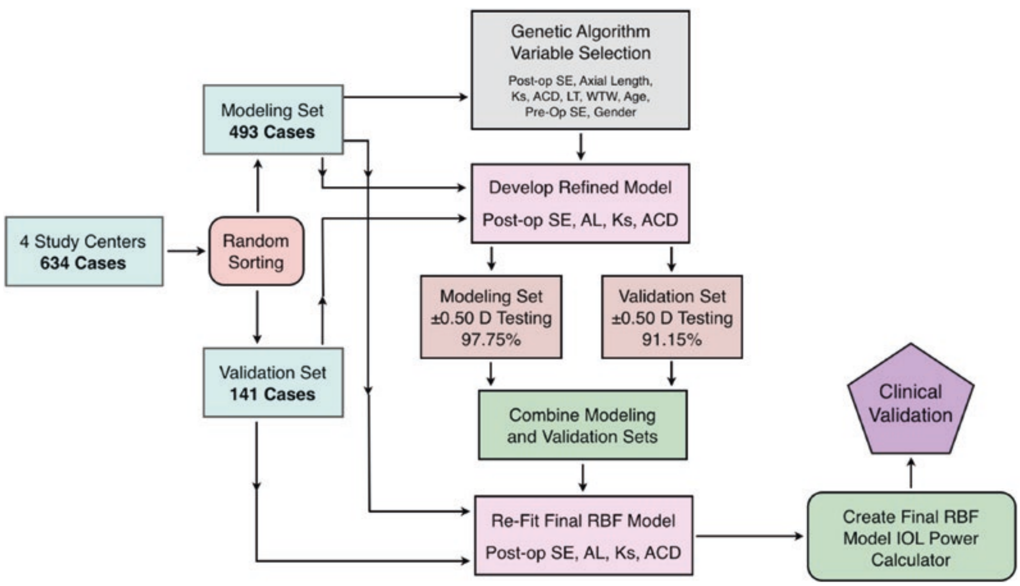


Fig. 42.3 The initial design for the creation of the Hill-RBF IOL power selection method

propagation cycle, and the output was adjusted until a maximum accuracy was obtained [11] (Fig. 42.2).

Our first experience showed several unanticipated features. First, we were able to take a cloud of data and reduce it to a straight line. Second, the calculation method showed no bias, indicating that the accuracy would be limited only by the quality and quantity of data. Whether this was a long eye, a short eye, or an eye with an unusual anterior segment, only the breadth and depth of the patient database mattered. The initial design for the creation of the Hill-RBF IOL power selection method is outlined in Fig. 42.3.

Boundary Models

One standard tool in engineering is the concept of a boundary model. The idea behind this is to identify a data range outer boundary edge, inside which will still result in a specific level of calculation accuracy.

Artificial intelligence-based predictions for many different applications routinely have such meta-models that make predictions about prediction accuracy. Far from being a restriction with the erroneous assumption that all out-of-bounds calculations are useless, a boundary model instead makes transparent the approach's limitations that other methods typically hide.

The boundary model for the Hill-RBF method was created by developing a surface in a four-dimensional space that separates the region where the training data guarantees a 90% prediction ±0.50 D accuracy from the area where no such guarantee exists. The four dimensions are 1. axial length, 2. anterior chamber depth, 3. mean keratometry, and 4. the predicted postoperative spherical equivalent. This surface can be visualized in the form of six pairwise boundaries, as shown in Fig. 42.4.

Those cases where all data points fall within all boundary models are identified as "in-bounds," and those where one or more of the data points fall outside any boundary model are identified as "out-of-bounds." The user is notified as to the boundary status of each calculation (Fig. 42.5).

Our initial experience showed Hill-RBF to be no worse when calculating out-of-bounds cases than other IOL calculation methods. Globally, the boundary model makes known the limitations of all technologies and can be used as an additional tool to manage patient expectations.

As the breadth and depth of the patient database increases, the surface of the four-dimensional space also increases, with a resulting decrease in the number of out-of-bounds indications. By the time version 3 was completed, enough patient data was available that even highly unusual eyes would give an in-bounds indication (Fig. 42.6).

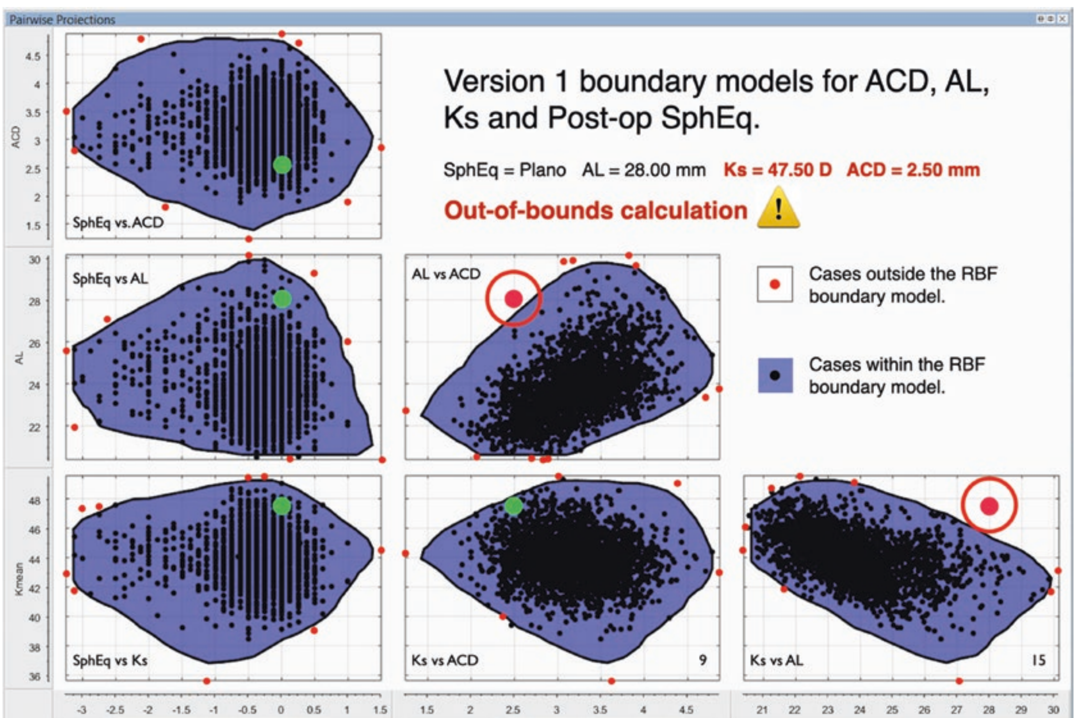


Fig. 42.4 The six pairwise boundary models used for version 1 of the Hill-RBF artificial intelligence IOL power selection method

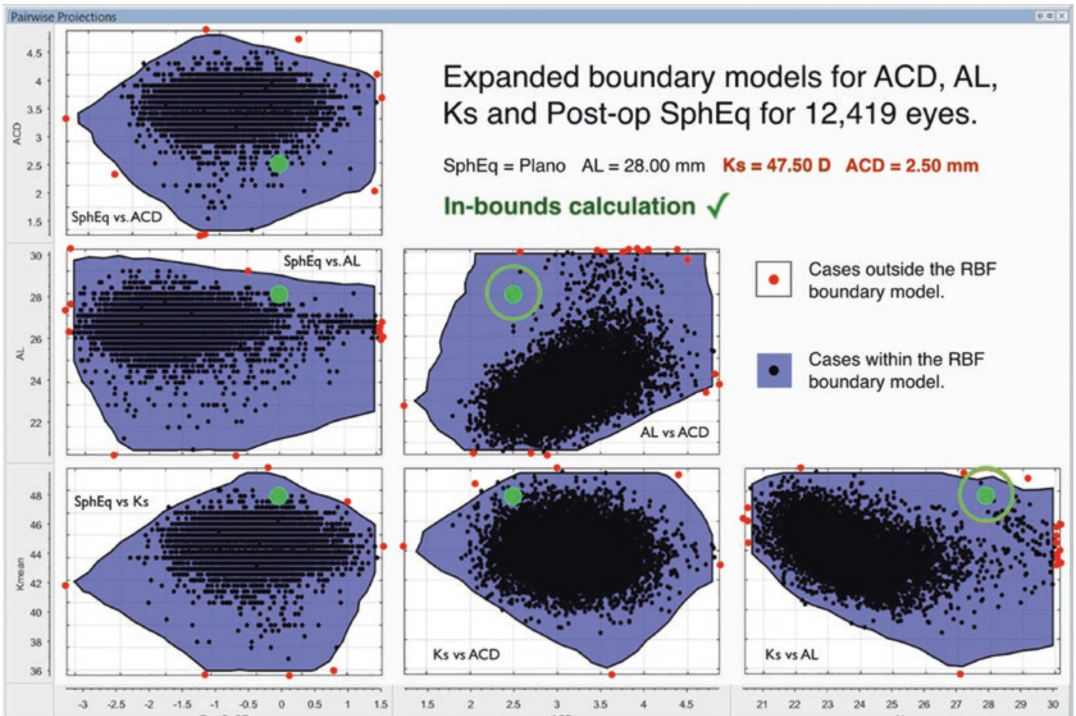


Fig. 42.5 Boundary model of version 2 of the Hill-RBF artificial intelligence IOL power selection method. Note how preoperative measurements that were out-of-bounds for version 1 are now in-bounds measurements for version 2

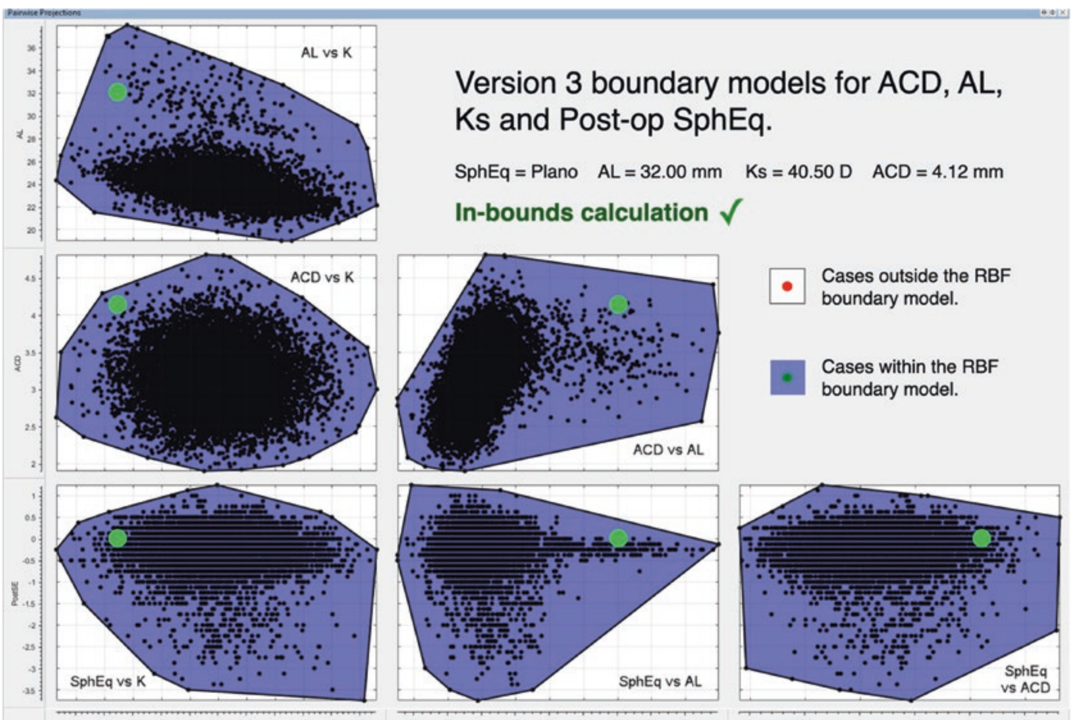


Fig. 42.6 The six pairwise boundary models for version 3 of the Hill-RBF artificial intelligence IOL power selection method. Note that for all preoperative measurements, a highly unusual eye still falls within the borders of each boundary model

A curious feature of the Hill-RBF method was that the in-bounds and the out-of-bounds accuracies were often similar for a wide range of surgeon datasets for the moderate to high axial hyperope.

First Prospective Study

By 2016, there was enough data to successfully create a useable artificial intelligence model and conduct a prospective study. This study consisted of 459 consecutive cases carried out at three independent study centers with an IOL power ranging from +7.50 D to +30.00 D, axial lengths ranging from 20.97 mm to 29.10 mm, a preoperative anterior chamber depth ranging from 2.13 mm to 4.59 mm, and a mean central corneal power ranging from 39.59 D to 48.06 D. The overall ±0.50 D accuracy for all cases in this study was 91.0% [17] (Fig. 42.7).

The following year, Roman and his group presented a study at the Los Angeles meeting of the American Society of Cataract and Refractive Surgery showing that the Hill-RBF method had a half-diopter accuracy of 92%, confirmation of the real-world accuracy and reproducibility of the boundary modeling process [18].

Availability to the Worldwide Ophthalmic Community

The initial success of this calculation method led to its inclusion within the Haag-Streit EyeSuite software. There was also created an online calculator at www.rbfcalculator.com for use by the worldwide ophthalmic community without charge [19].

By March 2018, a total of more than 12,000 eyes had been collected from our study centers around the world. This expanded dataset was refitted to a new artificial intelligence model as version 2, focusing on improved accuracy for the high axial hyperope and the addition of low power meniscus design intraocular lenses down to −5.00 diopters. This additional data also allowed for a greatly expanded boundary model. By 2023, approximately 15,000 caluclations were being performed on a weekly basis for the online version of the calculator.

By December 2020, the patient database had been further expanded and significantly refined, with improved accuracy for high axial hyperopes with IOL powers up to +34.00 diopters. There was also improved accuracy for eyes with odd combinations of anterior segment measurements such as unusual keratometry, horizontal corneal diameter, lens thickness, and the central corneal thickness (CCT).

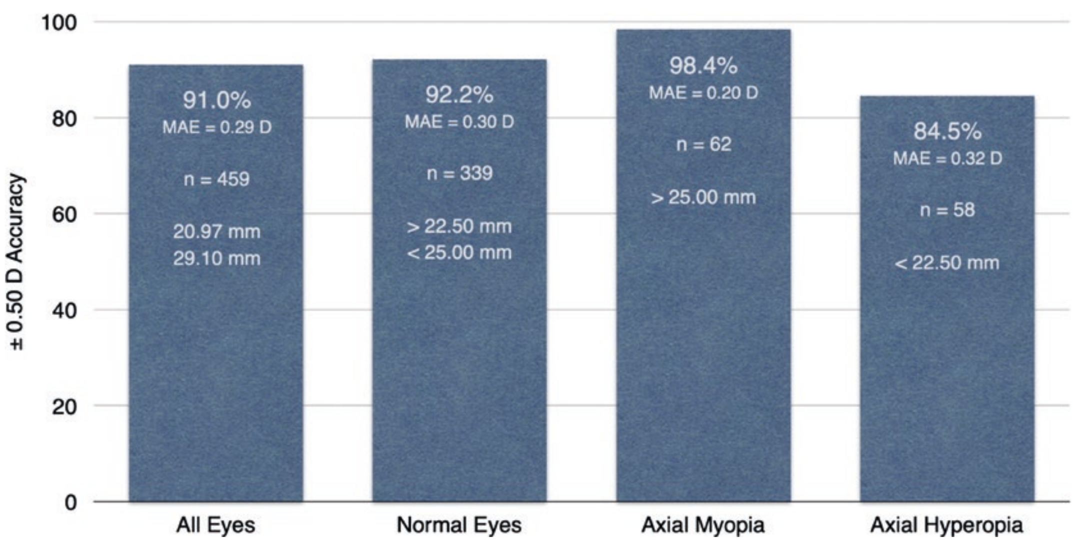


Fig. 42.7 The first prospective study using version 1 of the Hill-RBF artificial intelligence IOL power selection method

IOL	Cases	RBF 3	RBF 2	Barrett	Holladay I	SRK/T
SN60WF	301	89.6	89.5	89.1	86.6	82.0
SN60WF	668	88.7	88.6	88.1	86.4	84.9
Hoya 230	576	98.0	97.9	97.0	96.7	92.0
SN60WF	385	87.7	86.3	85.7	83.7	83.1
SN60WF	187	85.6	84.0	84.3	81.3	78.7
SN60WF	428	92.3	91.3	91.9	89.1	86.5
ZCB00	157	96.5	95.3	93.0	82.6	82.6
SN60WF	3,445	92.0	91.6	90.8	89.4	87.7
SN60WF	88	89.1	87.1	84.8	76.6	80.9
SN60WF	214	93.1	92.8	92.7	90.0	90.0
SN60WF	440	92.2	92.5	90.9	93.3	90.3
SN60WF	300	87.5	87.5	87.1	83.9	82.9
SN60WF	2,751	86.5	84.2	84.5	83.8	81.5
	9,940	**91.2%**	89.3%	87.3%	87.4%	85.3%

±0.50 D Weighted Averages

Fig. 42.8 Unpublished prerelease validation study of version 3 of the Hill-RBF artificial intelligence IOL power selection method

It should also be noted that artificial intelligence is capable of uncovering previously unappreciated relationships. The discovery that gender can exert an influence on IOL power is an example. Gender was also added as a calculation factor for version 3.

Currently, version 3 is available on the Haag-Streit Lenstar LS-900 and the online calculator at rbfcalculator.com. This most recent version has almost no out-of-bounds indications for normal eyes undergoing cataract surgery and a significantly reduced number of out-of-bounds presentations for unusual eyes.

During the validation process for version 3, a study was carried out of 9940 eyes not used to create the artificial intelligence model. Version 3 showed a weighted ±0.50 D accuracy of 91.2%. This level of accuracy is expected, given a 90% accuracy boundary model. Using this same database, version 2 of the RBF model had a ± 0.50 D accuracy of 89.3% (Fig. 42.8).

Current Accuracy

A study in the *Journal of Cataract and Refractive Surgery* concluded that version 3 of the Hill-RBF method has the lowest standard deviation and best overall ±0.50 D accuracy of the available

Formula	≤ 0.25 D			≤ 0.50 D			≤ 0.75 D			≤ 1.00 D		
	SS-OST (K)	SS-OST (TK)	OLCR (K)	SS-OST (K)	SS-OST (TK)	OLCR (K)	SS-OST (K)	SS-OST (TK)	OLCR (K)	SS-OST (K)	SS-OST (TK)	OLCR (K)
BUII	59%	57%	58%	92%	92%	91%	100%	99%	98%	100%	100%	100%
EVO 2.0	65%	62%	63%	92%	91%	91%	99%	99%	98%	100%	100%	100%
Haigis	65%	59%	54%	87%	88%	90%	98%	98%	99%	100%	100%	100%
HILL-RBF 2.0	62%	58%	56%	92%	90%	94%	99%	99%	96%	100%	100%	100%
HILL-RBF 3.0	68%	62%	62%	93%	95%	93%	100%	99%	99%	100%	100%	100%
Hoffer Q	54%	46%	48%	80%	81%	80%	93%	91%	95%	99%	99%	99%
Holladay 1	53%	53%	58%	80%	80%	81%	95%	93%	94%	100%	98%	98%
Holladay 2	48%	44%	-	79%	78%	-	96%	95%	-	99%	99%	-
Kane	66%	63%	53%	90%	91%	87%	99%	99%	98%	100%	99%	100%
SRK/T	54%	51%	54%	80%	81%	81%	95%	95%	92%	97%	99%	99%
Olsen	-	-	56%	-	-	84%	-	-	97%	-	-	99%

Fig. 42.9 The refractive accuracy of IOL power selection methods currently in use in 2021. (Tessler M, Cohen S, Wang L, et al. *J Cataract Refract Surg*. 2021 May 18 Published ahead of print. Used with permission)

Formula	SD										
Hill-RBF 3.0	0.266	1.000									
BUII	0.282	0.980	1.000								
EVO 2.0	0.285	0.980	0.980	1.000							
Kane	0.287	0.980	0.980	0.980	1.000						
Hill-RBF 2.0	0.290	0.031	0.980	0.980	0.980	1.000					
Haigis	0.311	0.080	0.980	0.980	0.980	0.980	1.000				
Holladay 1	0.367	0.000	0.000	0.002	0.001	0.000	0.142	1.000			
SRK/T	0.377	0.000	0.000	0.000	0.002	0.000	0.405	0.980	1.000		
Holladay 2	0.386	0.000	0.000	0.000	0.000	0.000	0.015	0.980	0.980	1.000	
Hoffer Q	0.387	0.000	0.000	0.002	0.000	0.000	0.000	0.980	0.980	0.980	1.000
		Hill-RBF 3.0	BUII	EVO 2.0	Kane	Hill-RBF 2.0	Haigis	Holladay 1	SRK/T	Holladay 2	Hoffer Q

Fig. 42.10 Comparison of a heteroscedastic standard deviation and the corresponding p-value of IOL power selection methods currently in use in 2021. (Tessler M, Cohen S, Wang L, et al. *J Cataract Refract Surg*. 2021 May 18 Published ahead of print. Used with permission)

calculation methods currently in use [20] (Figs. 42.9 and 42.10).

New Applications for Increased Sensitivity and Accuracy

During travels to Taiwan, Hong Kong, and mainland China, our Chinese colleagues told us that they were not happy with the accuracy of traditional vergence formulas developed using databases based mostly on Caucasian eyes.

Unpublished work by our teams has shown that the Chinese and Caucasian eyes appear to have subtle anatomic differences that influence IOL power selection. Mathematical tools with adequate sensitivity to detect subtle differences between Caucasian and Han Chinese eyes are now available.

Presently, a multicenter study is underway to develop an artificial intelligence model to improve IOL power selection accuracy for the Han Chinese eye [21, 22]. We now have study centers in the cities of Hangzhou, Guangzhou, Singapore, Hong Kong, and Taipei.

Challenges

An undeniable challenge is that any data-driven approach is only as good as the data used for its creation. We are grateful beyond words to the many surgeons who helped make Hill-RBF a success by contributing patient data.

Summary

The renowned Austrian American pianist Arthur Schnabel once said Mozart's piano sonatas are "too easy for children and too difficult for professionals." [23] For surgeons, the highly accurate outcomes of an artificial intelligence solution may seem simple. However, the complexity can push us to the edge of our abilities to develop these solutions.

As previously stated, a 78% ±0.50 D accuracy is typical using standard technology. With careful attention to preoperative measurement quality, ocular surface optimization, and more modern vergence formulas, this accuracy can improve to 84% or better. However, with the same attention to preoperative measurements, plus the addition of IOL power selection by artificial intelligence, the possibility of ±0.50 D accuracy of 90% is readily achievable.

We believe that the future of ophthalmology is bright. Incremental improvements in IOL power selection accuracy will eventually take us toward the goal of a 100% ±0.50 D accuracy.

Disclosures

Dr. Hill licenses the Hill-RBF method to Haag-Streit AG Switzerland for use on the Lenstar LS900.
Dr. Haehnle is an employee of Haag-Streit AG, Köniz, Switzerland.
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The online Hill-RBF IOL power calculator at *https://rbfcalculator.com* is provided without charge to the global ophthalmic community.

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