



# EVALUATING TECHNIQUES AND OUTCOMES IN CORNEAL ENDOTHELIAL PRESERVATION: A SYSTEMATIC REVIEW

<sup>1</sup>Nilima Ramteke, <sup>2</sup>Dev Hinduja, <sup>3</sup>Preksha Garg, <sup>4</sup>Vaishnavi Dixit

<sup>1</sup>Assistant Professor, <sup>2</sup>Scholar, <sup>3</sup>Scholar, <sup>4</sup>Scholar

Department of CSE (Artificial Intelligence & Analytics),

MIT School of Computing,

MIT Art, Design & Technology University, MIT ADT Campus, Pune Maharashtra INDIA

*Abstract:* Corneal disease, such as endothelial dysfunction and other dystrophies, are the leading causes of visual impairment and blindness worldwide. The mainstay of treatment for corneal disease is corneal transplantation. Unfortunately, the success of this approach is limited by restrictions in tissue availability and immune rejection as well as difficulties managing postoperative recovery. The advances in the diagnosis, treatment, and management of corneal disease have burgeoned due to the introduction of machine learning (ML) techniques. Although they have promising potential, existing ML models are encumbered by several challenges, including limited and imbalanced datasets, inconsistent data quality, lack of interpretability, and poor integration of multimodal data. These limit the accuracy and clinical utility of existing solutions. In this paper we review the current status of ML for corneal disease research, highlight challenges that are common in this space, and identify future directions that should be explored in order to address these challenges. Proposed approaches include data sharing and collaboration between research groups, improved data augmentation, advanced techniques such as transfer learning and few-shot learning, and interpretable models. Encouragement and consideration of such issues will motivate future ML studies to help establish a more reliable, generalizable, and clinically useful application of ML in corneal disease management.

*Index Terms* - Corneal diseases, machine learning, endothelial dysfunction, data augmentation, clinical validation

## I. INTRODUCTION

Corneal diseases, such as endothelial dysfunction and different forms of dystrophy, are considerable causes of vision impairment and blindness worldwide [1,2]. Corneal transplantation is therefore the gold standard treatment for patients with end-stage disease; however, light years of inadequate tissue availability, immune rejection, and issues in postoperative regimes prevent optimum outcomes for patients. The arrival of machine learning (ML) has offered a new path to enhance the diagnosis, treatment, and management of corneal conditions. However, although of great prospects, existing ML techniques have limitations towards small and imbalanced data sets, heterogeneous data quality, interpretative involvement of models, and insufficient integration of multimodal clinical information. These challenges markedly compromise the accuracy, generalizability, and clinical utility of ML models in this domain. To overcome these limitations, future research should promote collaboration to share data, enhance data augmentation methods, better manage class imbalance, and create more interpretable models. Other techniques such as transfer learning and few-shot learning for model training, and the use of multimodal input can increase the robustness and applicability of models in this domain. Moreover, real-world clinical validation of these models along with adherence to ethical guidelines and privacy regulations will be critical for the sustainable implementation of ML techniques in the management of corneal disease. Here we provide a discussion on the current state of ML

applications in corneal disease, the major challenges that exist, and recommendations for future work to overcome these barriers and advance the field.

## II. LITERATURE SURVEY

Rocha-De-Lossada et al. (2021) summarize recent progress in the optimization of corneal endothelial dysfunction management. The main issues are insufficient availability of high-quality endothelial tissue, and complications like graft rejection in corneal transplantation. The authors discuss cell-based therapies and tissue engineering strategies that may ameliorate these problems. Although further randomized clinical trials are needed to confirm the long-term efficacy of these new therapeutics, preliminary data are promising and represent an advancement in the treatment of corneal endothelial dysfunction. Borroni et al. Results of a multicenter registry by Ihl et al. (2021) also offer pragmatic guidance for improved DMEK outcomes. They draw resources from expert corneal transplant surgeons and provide "best practices" how to prepare the tissue, how to unfold the graft—step by step, written out to help both the novice and experienced surgeon. This effort is intended to streamline the DMEK learning curve and enhance transplant outcomes. Gain et al. (2016) give a global overview of corneal transplantation and eye banking and mention that corneal blindness is the third leading cause of blindness worldwide, affecting about 10 million people. They highlight the importance of eye banks in providing storage, quality, and safety of corneal tissues for successful transplantation. The legal, ethical, religious, and cultural obstacles to organ and tissue transplantation are also explored. However, the specific characteristics of corneal tissue allow its storage and transplantation more feasible in comparison with other tissues and organs. Grzybowski et al. (2019) assess complications of phacoemulsification cataract surgery in diabetics. They point to problems such as sluggish wound healing, aberrant epithelial basement membranes, and abnormal epithelial-stromal interactions. Diabetic patients present with other obstacles such as lower endothelial cell density and decreased pupil size, which make cataract surgery even more challenging. Hatou and Shimmura (2019) summarize methods for generating corneal endothelial cells from embryonic stem cells (ES) and induced pluripotent stem cells (iPS). There was a \$3.3 billion unmet global need for corneal transplantation in 2019, with only 185,000 corneal transplantations being performed in 116 countries yearly. They focus on regenerative therapies as an attractive alternative to existing transplantation methods. Adjievska (2023) explains the condition of the corneal endothelium following cataract surgery and its association with corneal edema. Endothelial cell loss postoperatively is also observed when rare entities like cornea guttata and Fuchs' dystrophy are present as risk factors. It has been suggested that specular microscopy should be a part of preoperative workup to predict surgical complications and to facilitate surgical planning. Vedana et al. (2016) discuss clinical manifestations, genetics and pathophysiology of Fuchs' endothelial corneal dystrophy (FECD), the most common reason for cornea transplantation. They also examine developments in endothelial keratoplasty and new therapeutic agents for FECD. Lundberg et al. (2005, 2024) explore postoperative corneal edema and how it correlates with endothelial cell loss after cataract surgery. These studies suggest that low preoperative endothelial cell density is a major contributor of postoperative outcomes, where low density increases the risk of permanent corneal decompensation. Ho and Afshari (2015) highlight recent advances in cataract surgery, including the use of viscous dispersive ophthalmic viscoelastic devices (OVDs) to protect the corneal endothelium. New OVDs look promising, but more work needs to be done to prove their effectiveness. Mencucci et al. Zyfko et al. (2006) find that standard phacoemulsification losses more endothelial cell count than MICS, where they identify age, nucleus grade, duration of phacoemulsification and ultrasound energy as determinants of endothelial damage. Abdallah et al. provide reference parameters for healthy Egyptian eyes—corneal endothelial cell density and morphology—among which corneal endothelial morphology has been studied in terms of different intraocular surgeries and corneal transplantation. Abell et al. (2012) discuss femtosecond laser-assisted cataract surgery and its potential for causing endothelial cell loss, citing the necessity to minimize fluid movement in the anterior segment to avoid complications like corneal edema. Yamazoe et al. (2011) evaluate cataract surgery outcomes in patients with low endothelial reserves, allowing surgeons to better contextualize the risks of bullous keratopathy and inform the timing of surgery for such patients. Li et al. (2019) study the therapeutic efficacy of corneal transplantation in cases of refractory corneal ulcer due to *Pseudomonas* sp. and report that lamellar transplantation is a beneficial option with good visual prognosis and less rejection rates compared to penetrating transplantation. Bruel et al. The involvement of MacCumber et al. (2009) in meta-analysis of OVD protective effect in cataract surgery, shows that endothelial cells loss depends on the parameters of surgery and degenerated lenses nucleus. Kumar et al. (2022) and Kahraman et al. (2007) state that the loss of endothelial cell in cataract surgery varies depending on the sources of phacoemulsification time, ultrasound energy, and surgical techniques. Moshirfar et al.

(2021) examine the outcomes of cataract surgery in patients with Fuchs' corneal dystrophy and recommend techniques for perioperative management and intraocular lens selection to help optimize outcomes. Tang (2024) describes femtosecond laser-assisted cataract surgery in post-penetrating keratoplasty patients, suggesting that femtosecond-assisted cataract surgery is predictable and safe in complex cases. Such reviews set the stage for a comprehensive understanding of the issues surrounding optimal management of corneal endothelial dysfunction, how cataract surgery may affect its course, and for the further development of surgical techniques and long-lasting implant technology. Cornea transplantation is one of the most commonly performed transplant surgery that has major roadblocks including, but not limited to shortage of quality endothelial tissue, graft rejection and dependency on eye banks. [20] Higher FTIR key parameters correlated with increased surface roughness, facilitating surgical complications associated with cataract surgery, including corneal endothelial cell loss, corneal edema, and delayed wound healing, aggravated by diabetes, older age, and high phacoemulsification energy. Poor postoperative outcomes also results from deficient diagnostic capabilities, including insufficient preoperative risk stratification tools. Novel treatments based on regenerative concepts such as stem cell-derived endothelial cell products represent exciting future directions but will need to be validated in the next few years in clinical studies. Femtosecond laser-assisted surgery and microincision cataract surgery offer promise for some improvement, but not yet optimized. Demographic diversity and ethical constraints across the world limit widespread access to advanced treatments.

**Table 1: Literature Survey of Various Studies on Corneal Diseases**

Sr. No.	Author(s)	Year	Dataset	Proposed Methodology for Evaluation
1.	Rocha-de-Lossada et al.	2021	Clinical case studies	Evaluate success rate of alternative therapies (cell-based and tissue engineering) in reducing endothelial dysfunction and rejection rates.
2.	Borroni et al.	2021	Surgical performance data	Compare procedural success rates and complications pre- and post-adoption of DMEK guidelines provided in the study.
3.	Gain et al.	2016	Eye bank registry data	Analyze successful corneal transplant outcomes in relation to eye bank practices and address barriers such as legal and ethical challenges.
4.	Grzybowski et al.	2019	Diabetic patient records	Evaluate postoperative complications like delayed wound healing and recurrent erosions in diabetic patients undergoing cataract surgery.
5.	Hatou & Shimmura	2019	iPS/ES cell differentiation	Measure differentiation efficiency and survival rates of derived corneal endothelial cells.
6.	Adjievska	2023	Cataract surgery data	Use preoperative specular microscopy predictions vs. actual postoperative outcomes for corneal edema and cell loss rates.
7.	Vedana et al.	2016	FECD patient data	Evaluate diagnostic accuracy of endothelial keratoplasty

				advancements and predictive markers in FECD patients.
8.	Lundberg et al.	2005	Cataract surgery outcomes	Correlate postoperative swelling metrics with endothelial cell loss, validated against long-term recovery data.
9.	Ho & Afshari	2015	Surgical records	Compare protective efficacy of viscous dispersive OVDs in cataract surgeries, focusing on postoperative endothelial density.
10.	Hwang et al.	2015	Cataract patient records	Model the impact of variables like ultrasound power and surgery time on endothelial loss rates.
11.	Mencucci et al.	2006	Phacoemulsification records	Compare endothelial damage metrics across standard and microincision cataract surgery techniques.
12.	Abdellah et al.	2019	Egyptian eye dataset	Establish baseline corneal endothelial metrics for Egyptian populations; accuracy not relevant for observational baseline study.
13.	Abell et al.	2012	Femtosecond vs. conventional data	Evaluate postoperative outcomes, focusing on fluid dynamics and endothelial preservation.
14.	Yamazoe et al.	2011	Low endothelial density cases	Assess complication rates and long-term recovery in low endothelial cell density patients undergoing cataract surgery.
15.	Li et al.	2019	Pseudomonas ulcer cases	Compare success rates and vision improvement between lamellar and penetrating corneal transplantation for bacterial ulcers.
16.	Bruel et al.	2009	OVD meta-analysis data	Aggregate and compare protective efficacy of different OVDs in minimizing endothelial cell loss.
17.	Briceno-Lopez	2023	Edema and cell loss records	Analyze correlations between preoperative diagnostics and postoperative outcomes in manual phacoemulsification cases.
18.	Ventura	2001	Cataract surgery thickness data	Monitor changes in corneal thickness and endothelial density over time, validating recovery trends.
19.	Lundberg	2024	Long-term surgical data	Evaluate endothelial changes over a 7-year period post-surgery; correlate outcomes with preoperative metrics.

20.	Kumar et al.	2022	Comparative surgery data	Compare cell loss and corneal thickness changes between phacoemulsification and small-incision techniques.
21.	Kahraman et al.	2007	Surgical trauma records	Analyze trauma and cell loss across bimanual and coaxial phacoemulsification techniques.
22.	Mathew et al.	2011	Diabetes-related cataract data	Compare endothelial damage metrics in diabetic vs. non-diabetic corneas post-surgery.
23.	Cho et al.	2010	Risk factor data	Model preoperative risk factors and correlate them with postoperative endothelial cell loss rates.
24.	Moshirfar et al.	2021	Fuchs' dystrophy cases	Assess perioperative techniques and lens placement optimizations for visual recovery.
25.	Tang	2024	Case reports	Evaluate visual recovery and refractive outcomes in femtosecond laser-assisted cataract surgeries after penetrating keratoplasty.

### III. LIST OF MACHINE LEARNING ALGORITHMS COMMONLY USED TO ADDRESS THE CHALLENGES

#### RELATED TO CORNEAL DISEASES

Machine learning algorithms are commonly used to address the challenges related to corneal diseases, surgical outcomes, and endothelial dysfunction

1. Convolutional Neural Networks(CNNs):  
In the analysis of images (corneal endothelial cell detection, segmentation of corneal diseases, and classification) (Fuchs' dystrophy, corneal edema, etc).
2. U-Net (and variants):  
CNN architecture is tailored to the medical domains for segmentation tasks like corneal layers or edematous regions
3. Support Vector Machines (SVMs):  
Commonly transfused for classification problems in which features (e.g., corneal cell parameters, surgical risks) are extracted manually or semi-automatically.
4. Random Forests:  
Well-suited for tasks like feature selection and classification (links- inference/classification of surgical results and/or endothelial cell loss).
5. K-Nearest Neighbors (KNN):  
Utilized for basic classification tasks based on corneal image or clinical data.
6. Artificial Neural Networks (ANNs):  
Nonspeculative neural networks to predict surgical outcomes and correlations across clinical parameters and risks
7. Long Short-Term Memory (LSTM) Networks:  
Time-series data, as in tracking corneal thickness or endothelial cell density over time after surgery.
8. Autoencoders:  
Applied on corneal images for anomaly detection, i.e. to find the non-regular pattern of cells or the variation in shape of the cornea.
9. Gradient Boosting Machines (e.g., XGBoost, LightGBM):  
Works well for tabular data to predict surgical complications or associate patient demographic with outcomes.

#### 10. K-Means Clustering:

When applied to aggregate corneal images, such as those of corneas, or endothelial cell patterns, could be used in unsupervised learning tasks of interest, such as disease subtype identification.

#### 11. Reinforcement Learning:

Investigated for the optimization of surgical techniques or the design of strategies to prevent endothelial cell loss during cataract surgery.

#### 12. Transfer Learning:

Utilising pre-trained models (e.g. ResNet, VGG, Inception) to address the challenge of limited datasets and enhance corneal disease classification or segmentation tasks.

### IV. SIGNIFICANT CHALLENGES FOR RESEARCHERS TO OVERCOME IN SOLVING THE ISSUES

Researchers face several **major challenges** in addressing the problems related to corneal diseases, endothelial dysfunction, and surgical outcomes:

#### 1. Limited Data Availability:

Imbalanced datasets due to rare corneal diseases/conditions lead to biased, non-generalized models across heterogeneous patient subgroups.

#### 2. Class Imbalance:

Rare corneal diseases or complications result in imbalanced datasets, leading to biased models that fail to generalize across diverse patient populations.

#### 3. Data Standardization:

Differences in imaging modalities (e.g. OCT, slit-lamp microscopy) and clinical protocols between different hospitals undermine the consistency and comparability of datasets.

#### 4. Small Sample Sizes:

Ophthalmology Medical datasets containing medical data are still limited because of ethical considerations, patient privacy, and the high cost of obtaining and annotating imaging data with high resolution.

#### 5. Complexity of Corneal Diseases:

The prediction and diagnosis of corneal conditions including Fuchs' dystrophy or endothelial cell loss are quite complex given the multifaceted nature of these conditions and the role of patient-specific factors.

#### 6. Dynamic Changes Post-Surgery:

Moreover, the dynamic nature of endothelial cell density and corneal thickness following surgeries makes it a challenge to predict the long-term results based on static preoperative data recommendations.

#### 7. Ethical and Legal Barriers:

Limitations due to data-sharing, privacy, and informed consent can restrict access to the rich and high-quality datasets vital for training these models.

#### 8. Generalizability of Models:

Machine learning algorithms trained on data pertaining to a single population or imaging device may not generalize to other demographics or clinical settings.

#### 9. Integration of Multimodal Data:

Integrating clinical (e.g., age, diabetes) and imaging data to enhance prediction performance is hard because these data are represented in varying formats and scales.

#### 10. Lack of Ground Truth:

Ground truth is often difficult to establish for all tasks, e.g. as with endothelial cell density estimation or corneal layer segmentation, which can be a subjective and time-consuming process.

#### 11. Computational Complexity:

In addition, since training deep learning models on high-resolution corneal images requires significant computational power, performing such experiments might not be possible for many researchers.

#### 12. Validation and Clinical Trials:

Bridging the gap from machine learning solutions to clinical practice involves extensive validation, randomized trials, and regulatory approvals of these solutions that can be time-consuming and resource-intensive.

#### 13. Adapting to Real-World Scenarios:

Many models ignore the real-world scenario with noisy or incomplete data, motion artifacts in imaging, or different surgical techniques. While this can be improved by forming standard datasets, better data

augmentation, transfer learning and interdisciplinary collaboration between researchers, clinicians and technologists.

Machine learning is a powerful tool to solve problems arising from corneal diseases, but it is not without its challenges. Such challenges can be overcome via collaborative building of large, diverse datasets involving different institutions or by leveraging techniques such as data augmentation or synthetic data generation to address limited sample sizes. Another effective approach treating the case with small datasets is transfer learning and few-shot learning approach. We can utilize techniques like SMOTE, focal loss, or cost-sensitive algorithms to tackle class imbalance. Adoption of standardized imaging protocols and domain adaptation reduces variability in imaging across centers or imaging machines, while the use of multimodal models has shown integration of imaging and clinical data for more robust and reproducible prediction. Want some ethical issues to be solved by federated learning and data privacy law adherence. Post operative with dynamics handled by time series models and eg. explainable AI for complex disease patterns. Generalization of the model is ensured by validation on diverse datasets, and real world testing, while pruning and quantization techniques improve computational efficiency. Finally, clinical trials and interpretable models engender trust and facilitate deployment into clinical practice.

## V. Future Research Directions to Overcome the Limitations of Existing Techniques in Corneal Disease Diagnosis and Treatment

- Data Sharing and Collaboration:** Encourage international collaboration between research institutions to develop large, diverse, high-quality datasets. Lending access to datasets through platforms along with privacy protection using federated learning or secure data sharing methods.
- Advanced Augmentation and Synthetic Data:** One approach to support rare diseases and underrepresented populations is to develop more sophisticated data augmentation techniques, such as 3D image transformations, as well as generative models (e.g., GANs) to create realistic synthetic data to improve model performance on these rare classes of data.
- Improved Handling of Class Imbalance:** Balance your data using better samplers such as adaptive synthetic sampling or focal loss. You can also use generative models to synthesize the minority class data.
- Standardization of Data and Protocols:** Work on uniform standards for imaging modalities, annotation techniques, and data collection protocols to maintain uniformity across datasets, enabling cross-study comparisons.
- Explainable AI:** Concentrate on creating models that provide interpretable predictions, like attention models or saliency maps, to allow clinicians to gain insights from AI predictions, enabling increased trust in and comprehension of AI predictions.
- Multimodal Integration:** Develop research methods that integrate multi-modal data (imaging, clinical, demographic, and genetic) in order to create more sophisticated and holistic models of corneal disease that better reflect the disease complexity.
- Transfer Learning and Few-Shot Learning:** Explore transfer learning to leverage pre-trained models on similar medical tasks and adopt few-shot learning techniques to train models effectively on smaller datasets while retaining accuracy.
- Real-Time Monitoring and Adaptation:** Create models receptive to real-time data using frameworks like online learning or reinforcement learning, where features from continuous monitoring of surgical recovery conditions can contribute to a personalized model post-surgery.
- Ethical and Privacy Considerations:** Build frameworks around consent of usage, anonymized or synthetic data usage to bypass privacy roadblocks, and ensure compliance with global laws like GDPR, HIPAA, etc.
- Validation in Clinical Settings:** Conduct multi-center validation studies for market adoption of diagnostic models in clinical setup, both for short and Long-term outcomes.

Addressing these challenges will allow for the advancement of more robust, interpretable, and clinically relevant machine learning solutions for the diagnosis and management of corneal diseases.

## VI. CONCLUSION

Corneal end-stage diseases remain a major cause of visual impairment despite advances in diagnostics, medical, and surgical treatments, leading to corneal transplantation and resulting in improper postoperative management, which might be improved by machine learning (ML) and artificial intelligence (AI) applications. However, barriers including limited and imbalanced datasets, heterogeneity in data quality, lack of model interpretability, and limited integration of multimodal clinical data will continue to prevent the widespread clinical application of ML in this domain. Future works should be directed towards overcoming these limitations by focusing on collaborative exchanging of data for large datasets, and data augmentation, as well as adopting new methods such as transfer learning and few shot learning methods for space resource data-rich scenarios. Additionally, the successful amalgamation and implementation of ML models for corneal disease management will be predicated upon the creation of more interpretable and robust models, the fusion of various sources of data, and the validation of ML models in clinical practice through large-scale clinical trials. These obstacles can ultimately hinder the potential of ML to transform the diagnosis and management of corneal diseases, thereby necessitating strategies to overcome such barriers to develop personalized and smart treatment approaches.

## REFERENCES

1. Abdellah, M., Ammar, H., Anbar, M., Mostafa, E., Farouk, M., Sayed, K., & Elghobaier, M. (2019). Corneal endothelial cell density and morphology in healthy Egyptian eyes. *Journal of Ophthalmology*, 2019, 1-8. <https://doi.org/10.1155/2019/6370241>
2. Abell, R., Kerr, N., & Vote, B. (2012). Femtosecond laser-assisted cataract surgery compared with conventional cataract surgery. *Clinical and Experimental Ophthalmology*, 41(5), 455-462. <https://doi.org/10.1111/ceo.12025>
3. Adjievska, B. (2023). Corneal edema after cataract surgery - changes in corneal endothelium cell characteristics. *Medis – International Journal of Medical Sciences and Research*, 2(2), 37-40. <https://doi.org/10.35120/medisij020237i>
4. Borroni, D., Lossada, C., Parekh, M., Gadhvi, K., Bonzano, C., Romano, V., ... & Rodríguez-Calvo-de-Mora, M. (2021). Tips, tricks, and guides in descemet membrane endothelial keratoplasty learning curve. *Journal of Ophthalmology*, 2021, 1-9. <https://doi.org/10.1155/2021/1819454>
5. Briceno-Lopez, C. (2023). Corneal edema after cataract surgery. *Journal of Clinical Medicine*, 12(21), 6751. <https://doi.org/10.3390/jcm12216751>
6. Bruel, A., Gailly, J., Devriese, S., Welton, N., & Shortt, A. (2009). The protective effect of ophthalmic viscoelastic devices on endothelial cell loss during cataract surgery: a meta-analysis using mixed treatment comparisons. *British Journal of Ophthalmology*, 95(1), 5-10. <https://doi.org/10.1136/bjo.2009.158360>
7. Cho, Y., Chang, H., & Kim, M. (2010). Risk factors for endothelial cell loss after phacoemulsification: comparison in different anterior chamber depth groups. *Korean Journal of Ophthalmology*, 24(1), 10. <https://doi.org/10.3341/kjo.2010.24.1.10>
8. Gain, P., Jullienne, R., Hé, Z., Aldossary, M., Acquart, S., Cognasse, F., ... & Thuret, G. (2016). Global survey of corneal transplantation and eye banking. *Jama Ophthalmology*, 134(2), 167. <https://doi.org/10.1001/jamaophthalmol.2015.4776>
9. Grzybowski, A., Kanclerz, P., Huerva, V., Ascaso, F., & Tuuminen, R. (2019). Diabetes and phacoemulsification cataract surgery: difficulties, risks and potential complications. *Journal of Clinical Medicine*, 8(5), 716. <https://doi.org/10.3390/jcm8050716>
10. Hatou, S. and Shimmura, S. (2019). Review: corneal endothelial cell derivation methods from es/ips cells. *Inflammation and Regeneration*, 39(1). <https://doi.org/10.1186/s41232-019-0108-y>
11. Ho, J. and Afshari, N. (2015). Advances in cataract surgery. *Current Opinion in Ophthalmology*, 26(1), 22-27. <https://doi.org/10.1097/icu.0000000000000121>

12. Hwang, H., Lyu, B., Yim, H., & Lee, N. (2015). Endothelial cell loss after phacoemulsification according to different anterior chamber depths. *Journal of Ophthalmology*, 2015, 1-7. <https://doi.org/10.1155/2015/210716>
13. Kahraman, G., Amon, M., Franz, C., Prinz, A., & Abela-Formanek, C. (2007). Intraindividual comparison of surgical trauma after bimanual microincision and conventional small-incision coaxial phacoemulsification. *Journal of Cataract & Refractive Surgery*, 33(4), 618-622. <https://doi.org/10.1016/j.jcrs.2007.01.013>
14. Kumar, R., Wahi, D., & Tripathi, P. (2022). Comparison of changes in endothelial cell count and central corneal thickness after phacoemulsification and small-incision cataract surgery. *Indian Journal of Ophthalmology*, 70(11), 3954-3959. [https://doi.org/10.4103/ijo.ijo\\_1906\\_22](https://doi.org/10.4103/ijo.ijo_1906_22)
15. Li, Y., Wang, T., Wang, Q., Jiang, S., & Wang, X. (2019). The therapeutic effect of corneal transplantation for refractory pseudomonas aeruginosa corneal ulcer.. <https://doi.org/10.21203/rs.2.17414/v1>
16. Lundberg, B. (2024). Corneal endothelial changes seven years after phacoemulsification cataract surgery. *International Ophthalmology*, 44(1). <https://doi.org/10.1007/s10792-024-03044-6>
17. Lundberg, B., Jönsson, M., & Behndig, A. (2005). Postoperative corneal swelling correlates strongly to corneal endothelial cell loss after phacoemulsification cataract surgery. *American Journal of Ophthalmology*, 139(6), 1035-1041. <https://doi.org/10.1016/j.ajo.2004.12.080>
18. Mathew, P., David, S., & Thomas, N. (2011). Endothelial cell loss and central corneal thickness in patients with and without diabetes after manual small incision cataract surgery. *Cornea*, 30(4), 424-428. <https://doi.org/10.1097/ico.0b013e3181eadb4b>
19. Mencucci, R., Ponchietti, C., Virgili, G., Giansanti, F., & Menchini, U. (2006). Corneal endothelial damage after cataract surgery: microincision versus standard technique. *Journal of Cataract & Refractive Surgery*, 32(8), 1351-1354. <https://doi.org/10.1016/j.jcrs.2006.02.070>
20. Moshirfar, M., Huynh, R., & Ellis, J. (2021). Cataract surgery and intraocular lens placement in patients with fuchs corneal dystrophy: a review of the current literature. *Current Opinion in Ophthalmology*, 33(1), 21-27. <https://doi.org/10.1097/icu.0000000000000816>
21. Rocha-de-Lossada, C., Rachwani-Anil, R., Borroni, D., Sánchez-González, J., Esteves-Marques, R., Soler-Ferrández, F., & Rodríguez-Calvo-de-Mora, M. (2021). New horizons in the treatment of corneal endothelial dysfunction. *Journal of Ophthalmology*, 2021, 1-11. <https://doi.org/10.1155/2021/6644114>
22. Tang, Q. (2024). Challenges in cataract surgery after penetrating keratoplasty managed using femtosecond laser: a series of 3 case reports. *Medicine*, 103(25), e38614. <https://doi.org/10.1097/md.00000000000038614>
23. Vedana, G., Villarreal, G., & Jun, A. (2016). Fuchs endothelial corneal dystrophy: current perspectives. *Clinical Ophthalmology*, 321. <https://doi.org/10.2147/ophth.s83467>
24. Ventura, A. (2001). Corneal thickness and endothelial density before and after cataract surgery. *British Journal of Ophthalmology*, 85(1), 18-20. <https://doi.org/10.1136/bjo.85.1.18>
25. Yamazoe, K., Yamaguchi, T., Hotta, K., Satake, Y., Konomi, K., Den, S., ... & Shimazaki, J. (2011). Outcomes of cataract surgery in eyes with a low corneal endothelial cell density. *Journal of Cataract & Refractive Surgery*, 37(12), 2130-2136. <https://doi.org/10.1016/j.jcrs.2011.05.039>