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Supporting Clinical Decision-Making in Optometry: OCT Imaging, Artificial Intelligence, and the Integration of Technology in Practice

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A dissertation submitted in partial fulfilment of the requirements for the degree of:

Doctor of Philosophy of **University College London**

Department of Medical Physics and Biomedical Engineering

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University College London

September 2025

Declaration

I, Josie Carmichael, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Acknowledgements

Firstly, I would like to thank the community optometrists who took part in the interview study, and the optometrists at Moorfields Eye Hospital who contributed to the research on decision making with AI support. I am deeply appreciative of the time you gave, the honesty with which you shared your experiences, and the thoughtful perspectives you brought to the discussions. Your contributions have been central to the insights presented in this thesis, and I am grateful for the trust you placed in me to represent your views.

My deepest gratitude goes to my primary supervisor, Professor Ann Blandford. You have shown me the importance of recognising and using one’s strengths, while providing the right balance of guidance and independence to encourage growth. I have learned a great deal from your expertise, your thoughtful mentorship, and your example of how to navigate the space between disciplines with clarity. It has been a privilege to be your final PhD student, and I am grateful for your support.

I would also like to thank my secondary supervisors, Professor Enrico Costanza and Professor Konstantinos Balaskas. Enrico, your expertise in Human-Computer Interaction and thoughtful contributions have broadened my perspective and strengthened my approach to research. Konstantinos, your clinical insight and deep understanding of ophthalmology have ensured that this work remains relevant and impactful to practice. I have valued our monthly meetings and all I have learned from you both.

Special thanks go to Professor Pearse Keane at Moorfields Eye Hospital, and to Reena Chopra and Marc Wilkins at Google, whose provision of data and code, along with their patience in answering my many queries, made a tangible difference to parts of this project.

This research was supported by the National Institute for Health and Care Research (NIHR) Biomedical Research Centre at Moorfields Eye Hospital NHS Foundation Trust and UCL Institute of Ophthalmology (grant number IS-BRC-1215-20002), and by the Engineering and Physical Sciences Research Council (EPSRC) (grant number EP/S021930/1). This work would not have been possible without their support.

To Dilisha Patel, thank you for being both a mentor and a friend. Your guidance through the highs and lows of PhD life, your feedback on my thesis, and your support beyond academia have meant so much to me. I am also thankful to the rest of Ann's research team, particularly Jeremy Opie, Julia Manning, Maura Bellio and Roxana Ramirez Herrera, for their constructive feedback during meetings and for helping me develop as a researcher.

I would also like to thank the i4health Centre for Doctoral Training at UCL, especially my fellow cohort members, for making the early stages of the PhD a shared journey. Particular thanks go to David Scobie for his friendship, and to Thomas Wemyss, whose technical expertise during our internship collaboration was a great learning experience.

To Aodhan Brownlee, thank you for providing some much-needed encouragement for the final stage of this process. To my dear friend, Ashleigh Trowill, thank you for being a constant source of emotional support during a challenging year. Your kindness, empathy and humour helped me through difficult times, and your friendship is truly one of a kind. I am also indebted to my oldest friend, Corey Holt, whose own PhD journey inspired me to begin mine and whose encouragement has been a source of motivation.

To my parents, my grandparents and my sister Nia in Wales, thank you for always encouraging me and celebrating my achievements with pride.

And finally, to my son, with me through my viva. I can't wait to meet you.

Abstract

Ophthalmic services in the UK face increasing pressure, with referrals from primary care optometrists contributing to hospital eye service demand. Optical coherence tomography (OCT) enables earlier detection of retinal abnormalities but can also highlight benign findings that drive false-positive referrals. These challenges have prompted interest in artificial intelligence as a form of clinical decision support (AI-CDSS).

This thesis used a mixed-methods approach to investigate both the clinical and human-computer interaction aspects of optometrists' referral decision-making with OCT and the potential role of AI-CDSS. A quantitative systematic review evaluated referral accuracy and found significant variation between conditions, with false-positive rates decreasing with experience (6.2% per year since registration, $p < 0.001$). A second mixed-methods review examined interventions to reduce false positives, showing variable effectiveness and underscoring the potential of AI.

Interviews with 20 primary care optometrists explored how OCT is integrated into practice, how referral decisions are made, and how AI-CDSS could be best designed. Four distinct practitioner profiles were identified: Newly qualified (Type 1), OCT-integrated (Type 2), experienced hesitant (Type 3), and experienced early adopters (Type 4). These profiles reflect differences in experience and confidence. Thematic analysis highlighted the interplay of clinical, contextual, and patient-specific factors in referrals. Another novel contribution is the application of proactive and reactive information-seeking behaviours to OCT interpretation: proactive seeking benefits from tools that support anticipation and learning, while reactive seeking requires immediate support at the point of uncertainty.

The thesis also examined optometrists' interactions with AI in ambiguous cases. A reanalysis of quantitative data showed that AI outputs, particularly segmentation overlays, influenced diagnostic confidence and trust even when inaccurate. While valued as interpretative aids these findings highlight the importance of careful output design.

This research advances HCI by deriving design considerations for safe and usable AI systems in primary care optometry. It contributes to optometry by characterising real-world OCT use and identifying practitioner experiences and learning patterns that shape diagnostic decision-making and information needs. Together, these findings provide actionable insights for the responsible design and deployment of AI-CDSS in primary eye care.

Impact Statement

Eye health is one of the fastest growing areas of demand within the NHS, with HES now managing more outpatient activity than any other specialty. This demand places increasing strain on services and is linked to delays in care that can result in avoidable sight loss. Primary care optometrists play a central role as the first point of contact for patients with eye concerns; however they contribute to high volumes of referrals, many of which do not require specialist intervention. The wider availability of technologies such as OCT has advanced what can be detected in community practice but can increase diagnostic uncertainty. These challenges highlight the need for practical solutions that can improve referral quality and make better use of NHS capacity.

This research focuses on the specific use case of decision-making in primary care optometry, where difficulties in interpreting OCT imaging and variability in access to support present significant challenges. These difficulties, compounded by time pressure and diagnostic uncertainty, highlight an area of clinical practice that could benefit substantially from well-designed artificial intelligence (AI-CDSS). While grounded in optometric practice, the findings and recommendations have relevance for other clinical domains where imaging interpretation and real-time decision-making are similarly complex.

By assessing optometrists' current reported practices with OCT imaging and their information-seeking behaviours, this research provides critical insights into how AI can be effectively integrated into clinical workflows. The in-depth interview study demonstrates that AI-CDSS tools must align with the ways optometrists currently seek and use information, offering support that complements rather than disrupts existing practices. This alignment is key to fostering trust and usability, ensuring that AI systems can support clinical decision-making in a practical, context-aware manner. Through a reanalysis of quantitative study data, this research presents evidence of how optometrists' clinical decision-making can be influenced by AI-CDSS outputs, for cases which are considered ambiguous or 'edge cases'.

Through a systematic review of existing literature and empirical investigation, this research offers new insights into the relationship between clinical experience, information needs, and trust in technological tools. By exploring how optometrists interact with AI-CDSS in realistic scenarios, the thesis identifies key factors that influence acceptance, including explainability, perceived accuracy, and the timing of AI support within the clinical workflow.

The societal and clinical impact of this research lies in its potential to improve decision-making in optometry, reducing diagnostic errors and enhancing patient care. The recommendations emerging from this study, emphasising transparency, contextual relevance, and alignment with real-world practice, provide guidance for developers of AI technologies aimed at supporting clinicians. Economically, more efficient decision-making may contribute to better resource allocation in primary care and help alleviate pressure on secondary care services.

In summary, this thesis contributes to the growing field of human-AI interaction in clinical environments by connecting AI design directly to the realities of optometric practice. While focused on a specific use case, the findings offer transferable lessons for other healthcare domains, demonstrating how AI can be developed to support clinicians in complex, high-stakes decision-making tasks.

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https://www.nature.com/articles/s41598-024-55410-0

u) **Publication name (e.g. journal or textbook):**

Journal

v) **Publisher name (e.g. Elsevier, Oxford University Press):**

Scientific Reports (Nature)

w) **Date of publication:**

21/04/2024

x) **List all authors as they appear in the publication:**

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List of Publications

Work in this thesis has been published in several peer-reviewed journals:

Carmichael J, Costanza E, Blandford A, Struyven R, Keane PA, Balaskas K. Diagnostic decisions of specialist optometrists exposed to ambiguous deep-learning outputs. Scientific Reports. 2024 Mar 21;14(1):6775.

Carmichael J, Abdi S, Balaskas K, Costanza E, Blandford A. The effectiveness of interventions for optometric referrals into the hospital eye service: A review. Ophthalmic and Physiological Optics. 2023 Nov;43(6):1510-23.

Carmichael J, Abdi S, Balaskas K, Costanza E, Blandford A. Assessment of optometrists' referral accuracy and contributing factors: A review. Ophthalmic and Physiological Optics. 2023 Sep;43(5):1255-77.

The following was presented a peer-reviewed doctoral consortium paper at a high-ranking International Human-Computer Interaction conference (CHI):

Carmichael J. Translating Human-Centred Artificial Intelligence for Clinical Decision Support Systems into Practice: A Medical Retina Case Study. In Extended Abstracts of the CHI Conference on Human Factors in Computing Systems 2024 May 11 (pp. 1-5).

The following was presented as a poster presentation at a high-ranking International Ophthalmology conference:

Carmichael J, Costanza E, Balaskas K, Keane PA, Blandford A. The Influence of Automated Support on Optometrists' Interpretation of Retinal OCT Scans. Investigative Ophthalmology & Visual Science. 2022 Jun 1;63(7):191-F0038.

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Glossary of Terms

AI – Artificial Intelligence

AI-CDSS – Artificial Intelligence Clinical Decision Support Systems

AMD – Age-Related Macular Degeneration

ANOVA – Analysis of Variance

ART – Aligned Rank Transform

AUC – Area Under the Curve

BCVA – Best Corrected Visual Acuity

CDSS – Clinical Decision Support System

CET – Continuing Education and Training

CI – Confidence Interval

CUES – COVID-19 Urgent Eyecare Service

DR – Diabetic Retinopathy

ERM – Epiretinal Membrane

FVDR – First Visit Discharge Rate

GA – Geographic Atrophy

GOC – General Optical Council

GOS – General Ophthalmic Services

GP – General Practitioner

HCI – Human–Computer Interaction

HES – Hospital Eye Service

IOP – Intraocular Pressure

IP – Independent Prescribing

KC – Keratoconus

MECS – Minor Eye Conditions Service

MEH – Moorfields Eye Hospital

ML – Machine Learning

mtmDR – More-Than-Mild Diabetic Retinopathy

NHS – National Health Service

NICE – National Institute for Health and Care Excellence

OCT – Optical Coherence Tomography

PAC – Primary Angle Closure

PACG – Primary Angle Closure Glaucoma

PACS – Primary Angle Closure Suspect

PED – Pigment Epithelial Detachment

PPV – Positive Predictive Value

PRISMA – Preferred Reporting Items for Systematic Reviews and Meta-Analyses

RCT – Randomised Controlled Trial

RPE – Retinal Pigment Epithelium

SIGN – Scottish Intercollegiate Guidelines Network

Chapter 1. Introduction and Overview of Thesis

AI technologies in healthcare have advanced rapidly over recent years and are being applied to tasks such as early diagnosis, risk stratification, and treatment planning (1). Many systems have demonstrated high diagnostic accuracy, yet the dominant research focus has been on comparing AI performance with human experts. While informative, such comparisons often neglect the reality that AI is unlikely to replace clinicians (2), and instead should be designed to work alongside them (3). Human-AI collaboration has been shown to improve performance over either party alone in some contexts (2), and research increasingly suggests that user trust, control, and understanding are key to successful adoption. For example, studies have shown that allowing clinicians some level of control over algorithmic decisions can reduce aversion to AI systems and increase willingness to adopt them as described by Dietvorst et al (4).

As a result, researchers in Human-Computer Interaction (HCI) and clinical AI implementation have emphasised the importance of user-centred design (4), ensuring that AI systems support, rather than override, clinical judgement. However, designing usable and trustworthy AI-CDSS tools for healthcare remains complex (5). Barriers include concerns about data quality, regulation, cost, ethical considerations, and most notably, stakeholder acceptance (6). Clinician scepticism and fear of workflow disruption are common barriers to implementation (7), making it essential that new systems are not only accurate but also intuitive and seamlessly integrated into clinical practice.

This thesis explores how such HCI issues can arise in the context of OCT imaging in primary care optometry. It focuses on how optometrists currently manage diagnostic uncertainty and how AI-CDSS tools could be designed and implemented to support image interpretation in this setting. By addressing both clinical and human-computer interaction perspectives, the research aims to inform the development of AI systems that are not only technically capable but also practical, acceptable, and useful for community optometrists.

1.1 Background

In the UK, NHS eyecare is generally delivered through a two-tier system. The first tier is primary care optometry, delivered in the community by optometrists who provide sight tests, manage minor eye conditions, and play a crucial role in the early detection of ocular disease. When a condition requires further investigation or treatment, such as suspected retinal pathology or unexplained visual symptoms, optometrists generally refer patients to the Hospital Eye Service (HES). This is the secondary care component of the UK National Health Service (NHS) responsible for delivering specialist ophthalmic care. These secondary care services, delivered by specialist ophthalmology teams, are responsible for diagnosis, monitoring, and treatment of more complex or serious conditions. This referral-based model relies on the clinical judgement of community optometrists to triage patients effectively, ensuring that those who need specialist care are seen promptly while minimising unnecessary pressure on limited HES capacity (8).

In recent years, demand for HES has increased substantially, driven by an ageing population and rising prevalence of chronic eye conditions (9). This increase in demand has underscored the importance of improving referral quality and ensuring appropriate use of specialist resources. Meanwhile, technological innovation, particularly in ocular imaging, has expanded the diagnostic capabilities available to community optometrists. Among these technologies, OCT has become especially prominent. OCT provides high-resolution, cross-sectional images of the retina and deeper ocular structures (Figure 1), allowing detection of subtle pathological changes that may not be visible using traditional imaging methods. OCT's clinical utility has made it the most frequently used imaging modality in many HES settings. At Moorfields Eye Hospital, for example, a 2017 audit found that over 1,000 OCT scans were performed daily across its main and satellite clinics (10), reflecting OCT's central role in modern ophthalmic diagnosis and disease monitoring.

Originally introduced in secondary care, OCT has now been widely adopted by primary care optometry. This expansion has been enabled by growing commercial availability and significant investment by high-street providers. For instance, in 2017, Specsavers Opticians announced a national programme to install OCT devices in each of its UK practices (11). The integration of OCT into community optometry allows earlier detection of conditions such as macular degeneration, glaucoma, and diabetic retinopathy, and has been shown to improve diagnostic sensitivity. A clinical vignette study by Jindal et al. (12) found that the addition of OCT to fundus imaging significantly improved optometrists' ability to identify retinal and optic nerve abnormalities-from 62% to 80% diagnostic accuracy. However, the study did not assess the impact of OCT on referral behaviour.

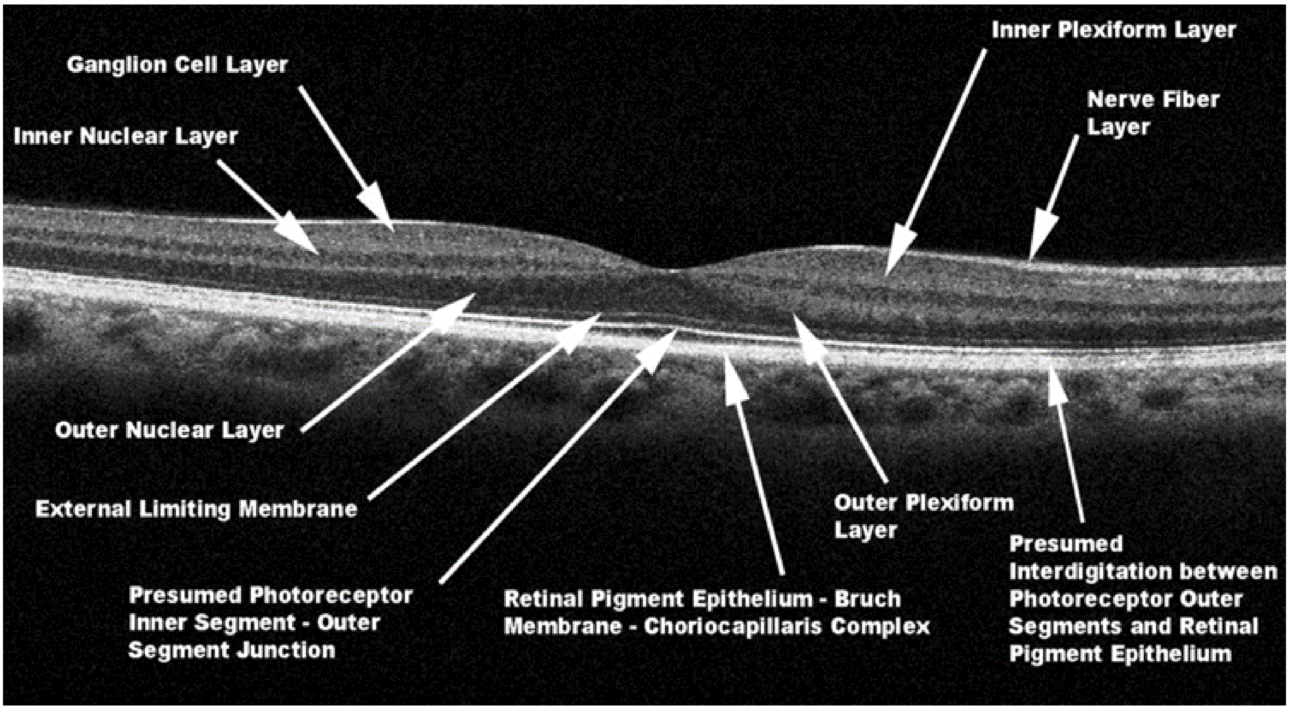

Figure 1: A cross-sectional 2-D Image of a healthy subject, taken using Spectralis optical coherence tomography (OCT). Retinal layers have been labelled using arrows. Used with permission (13).

While the increased use of OCT in primary care has clear benefits, it also presents potential challenges. Interpreting OCT images can be complex, and variation in training and experience may influence how confident practitioners feel in their assessments. Reduced diagnostic confidence may, in turn, encourage more cautious management decisions, which could contribute to additional referrals into HES. Alongside the growing volume of imaging, these factors suggest a possible role for support tools that aid interpretation and assist clinicians in making accurate decisions.

One such solution may lie in artificial intelligence-driven clinical decision support systems (AI-CDSS). These systems, when applied to ocular imaging such as OCT, have the potential to support clinicians by detecting and highlighting relevant features, suggesting possible diagnoses, or recommending appropriate management options (14). With the increasing development and availability of such tools, it is important to understand how they could be effectively integrated into primary care optometry.

This thesis aims to address key research gaps concerning the integration of OCT imaging into primary care optometric practice. It focuses on understanding how optometrists currently use OCT imaging to support clinical decision-making and how they seek information when faced with uncertainty. Additionally, the project addresses the translational challenges of implementing artificial intelligence (AI) tools, specifically clinical decision support systems (AI-CDSS), into real-world optometric workflows.

1.2 Research Questions

The research was structured around the following questions, divided into two thematic areas: clinical practice and OCT integration, and human-computer interaction.

1.2.1 Clinical Practice and OCT Integration

To determine the potential role of OCT technology and AI, it was necessary to first understand the clinical context in which such systems would operate. This meant examining the challenges faced by optometrists in diagnosing and managing retinal disease, the role of OCT in practice, and the factors contributing to false-positive referrals into HES. These insights provide the foundation for understanding both the opportunities and limitations of introducing AI into primary care optometry.

> ***RQ1. How accurate are referrals from primary care optometrists, particularly in relation to retinal conditions?*** This question was addressed through a systematic review that evaluated the accuracy of referrals originating from primary care optometric practice, with a particular focus on false-positive referrals.
>
> ***RQ2. What strategies have previously been used to reduce the number of false-positive referrals from optometrists to secondary care ophthalmology and have they been successful?*** This question was explored through a second systematic review that synthesised evidence on interventions and system-level approaches aimed at improving referral quality.
>
> ***RQ3. How do optometrists experience and use OCT imaging in their day-to-day clinical practice, particularly in the management of patients with suspected retinal disease?*** This question was explored through an in-depth

qualitative interview study, with primary care optometrists, that investigated how OCT findings are interpreted and incorporated into primary care eye examinations.

RQ4. Where do optometrists currently seek information or support when faced with clinical uncertainty regarding OCT findings, and why are sources favoured? This aspect of the in-depth interview study focused on understanding the role of reactive information-seeking behaviours in practice, and the perceived value of various information sources including peers, online tools, and referral pathways.

1.2.2 Human-AI Interaction and Implementation of AI-CDSS

Having established the clinical challenges associated with OCT use in primary care, the next stage of the research focused on the design and implementation of AI-CDSS tools to address these issues. A key consideration is that AI outputs can be presented in a variety of formats. This research therefore explored the design space of AI-CDSS outputs, examining how presentation format, timing within the consultation, and potential risks such as over-reliance or misinterpretation influence optometrists' interaction with AI.

RQ5. How do optometrists' diagnostic decisions and trust in AI-CDSS change when exposed to ambiguous or incorrect AI outputs, and what is the impact of different presentation formats such as segmentation overlays?

This was explored through a reanalysis of quantitative study data focusing on the behavioural effects of various AI visualisations and their influence on diagnostic accuracy, confidence, and trust. This question was also investigated as part of the in-depth interview study with a focus on issues such as trust calibration and the importance of transparency and explainability in AI interfaces.

RQ6. How should outputs from an AI-CDSS be displayed to ensure they are clinically useful for optometrists?

This question investigated optometrists' preferences for visual formats, content types, and the interpretability of AI-generated findings in practice during the in-depth interview study.

RQ7. At what point in the optometric consultation should an AI-CDSS for OCT interpretation be introduced to align with clinical workflows?

This research question examined where within the typical patient journey AI tools could be positioned to support, rather than interrupt, existing clinical reasoning and decision-making processes. This aspect of AI integration was investigated as part of the in-depth interview study.

Overall, these questions were addressed through a mixed-methods approach comprising systematic reviews, a reanalysis of quantitative study data and in-depth interviews with UK-based primary care optometrists. Together, they inform recommendations for a human-centred AI-CDSS aimed at supporting OCT interpretation in optometric care.

1.3 Structure of Thesis

The thesis is structured as follows:

Chapter 2 presents a systematic review evaluating the accuracy of referrals from primary care optometrists. It explores the prevalence of false-positive referrals and the factors that may influence referral quality.

Chapter 3 reviews existing interventions aimed at improving the quality of optometric referrals, such as enhanced referral schemes, feedback mechanisms, and the use of teleophthalmology. It assesses the outcomes, limitations, and implementation considerations of these strategies.

Chapter 4 provides a review of the relevant literature that informed the design and direction of the AI-CDSS aspects of the thesis. It focuses on human-computer interaction principles and includes a specific emphasis on AI systems developed for ophthalmology applications. The chapter explores concepts such as clinical trust in AI, cognitive bias, interface design, and explainability in clinical decision-making.

Chapter 5 presents a quantitative study reanalysing data from a previous project investigating how optometrists respond to ambiguous or incorrect outputs from an AI-CDSS. It explores the impact of different presentation formats, such as the inclusion of segmentation overlays, on diagnostic accuracy, confidence, and trust in the system.

Chapter 6 outlines the methodology used for the in-depth interview study conducted with UK-based primary care optometrists. It describes the study design, participant recruitment, interview procedures, and the approach taken to thematic analysis.

Chapters 7 to **9** present the findings from the thematic analysis of the qualitative data collected as part of the in-depth interview study.

Chapter 7 examines how OCT is positioned within different clinical workflows and how its use varies according to optometrists' levels of experience and confidence. It considers how OCT findings shape complex management decisions and introduces typologies of optometrists based on their practice style and reliance on OCT.

Chapter 8 explores how optometrists seek and apply information in response to clinical uncertainty, with a particular focus on OCT interpretation. It distinguishes between reactive and proactive information-seeking behaviours and draws on reflective models, such as Schön's, to examine how optometrists integrate new knowledge into their clinical decision-making.

Chapter 9 synthesises insights from the interview data to explore how AI-CDSS tools should be designed to align with real-world optometric practice. It addresses preferences for AI output design, the timing of information delivery, and the conditions under which optometrists are likely to trust and use AI systems. It proposes key design principles for successful integration.

Chapter 10 brings together findings from across the thesis to address the overarching research questions. It reflects on the clinical and practical implications of the results, the challenges of implementing AI-CDSS tools in optometric settings, and opportunities for future research and system development.

Chapter 2: Assessment of optometrists' referral accuracy and contributing factors: A review

Parts of this Chapter have been published in the following paper:

Carmichael J, Abdi S, Balaskas K, Costanza E, Blandford A. Assessment of optometrists' referral accuracy and contributing factors: A review. Ophthalmic and Physiological Optics. 2023 Sep;43(5):1255-77.

2.1 Introduction

In the UK, the majority of referrals into HES originate from optometric examinations in primary care, with one study carried out in Bradford, UK finding this proportion to be 72% (15). The General Optical Council (GOC) standards of practice guidelines state that optometrists should "recognise and work within the limits of their scope of practice" and "be able to identify when they need to refer a patient in the interests of the patient’s health and safety, and make appropriate referrals" (16); thus, optometrists should refer any condition that they feel unable to manage in practice. However, it is thought that many optometrists' referrals can be considered 'false-positives', meaning that these patients could safely be managed in primary care (12, 17). High rates of false-positive referrals are often reported as a contributing factor to the oversubscription of hospital eye clinics and several studies have assessed the accuracy of referrals for various eye conditions. However, until now, no in-depth review of referral accuracy from optometrists or the factors that may affect this has been conducted.

This review aimed to evaluate the accuracy of referrals originating from primary care optometric practices as well as the factors that may contribute to optometrists' level of accuracy. This review had the following specific objectives:

1. To synthesise studies assessing the accuracy of referrals from primary care optometric practices to secondary care ophthalmology across different countries.

2. To assess for which ocular condition(s) referrals are the most and least accurate.

3. To identify the factors which may affect the accuracy of referrals from optometrists into secondary care ophthalmology.

2.2 Methods

2.2.1 Registration

The international prospective register of systematic reviews (PROSPERO) was used to register the review protocol (registration number: CRD42022328721) to prevent duplication and to increase the transparency of the review process.

2.2.2 Eligibility Criteria

To complete a robust systematic search and selection of studies, a checklist of inclusion and exclusion criteria was created. This was to ensure consistency when screening articles and to act as a reference point when making decisions about whether to include/exclude articles. The decision was made to exclude studies that assessed referrals from diabetic retinopathy screening programmes. This decision was made as although many optometrists work as diabetic screening graders, and make referral decisions, this pathway does not represent the typical referral pathway from primary care optometry practices. Table 1 summarises the inclusion and exclusion criteria checklist respectively. Articles were screened for their suitability against these criteria.

Primary studies that used a quantitative design and were written in English were included. Studies were not excluded based on assessment of methodological limitations but the information about methodological limitations was used to assess confidence in the findings. Abstracts without a corresponding full paper were excluded, as they were unlikely to provide sufficiently rich data.

2.2.3 Search Strategy

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was used to help guide protocol development (18). PUBMED, MEDLINE and CINAHL were searched for potential studies for inclusion. Initially, a search was also performed using Google Scholar, however this returned a large number of irrelevant results, with relevant papers being duplicated from the other databases. Search strategies were developed for the databases. Studies published during or after December 2001 were included to ensure an assessment that is representative of recent practice. Table 2 presents the final facets and keywords used when searching databases. In addition to database searching, the reference lists of all included studies were reviewed and other key references which allows a method of 'reference chaining'.

Criteria	**Inclusion**	**Exclusion**
Time Period	Dec 2001-Dec 2022	Prior to Dec 2001
Language of study	English	Any other language
Study Design	Quantitative studies of current practice including (but not limited to): controlled, uncontrolled studies, surveys, retrospective analysis, clinical vignettes. Mixed-methods studies with a quantitative element.	Qualitative studies. Interventions in pilot studies, viewpoints, editorials, conference/meeting abstracts, expert opinions and grey literature. Systematic or similar reviews (e.g. narrative, scoping and realist reviews).
Setting	Any setting involving primary eye care	Internal referrals within secondary care, GP referrals.
Participants	Studies focussing on primary care optometrists making referrals to secondary care.	Studies focussing on referrals from GPs, other allied health professionals or patients who self-refer (e.g. patients attending A and E without a recommendation from an optometrist).
Condition focus	Any eye condition or conditions which have been referred to the hospital (can include anterior and posterior eye conditions).	Referrals by optometrists to non-ophthalmology services due to systemic conditions showing signs in the eye (e.g. referral to GP for blood pressure check). Referrals from diabetic retinopathy screening programmes.
Topic focus	Quantitative assessment of: 1. The % or number of referrals that are correct/incorrect from optometrists. 2. The individual factors affecting the accuracy of referrals from optometrists	Assessment of referral letter quality. Assessment of the source of referral e.g. "of all glaucoma referrals, 80% come from optometrists" but no assessment of whether these are correct/incorrect. Studies that have not assessed referrals from optometrists separate from other sources i.e. all referrals from primary care are assessed.

Table 1: Summary of the inclusion/exclusion criteria

Number Assigned to Facet	Facet	Keywords	Boolean
1	Optometrist	1. Optometrist(s) OR 2. Optometry OR 3. Primary eye care OR 4. Primary eye clinic(s) OR 5. Optician(s)	1 AND 2
2	Referral Practice	1. Referral(s)	

Table 2: Facet terms and their keywords used for database searching

2.2.4 Selection Process

All articles identified from database searches were organised in EndNote and duplicates were removed. The primary researcher (JC) conducted screening of the title and abstracts of all search results. A second researcher (SA) also screened all titles and abstracts. An initial sample of 20% was first screened by both researchers to assess agreement. All articles where the researchers disagreed were reviewed together and differences in interpretation of the inclusion/exclusion criteria were discussed. The remaining studies (80%) were screened by both researchers independently with a good level of agreement (kappa=0.82). Studies where the two reviewers disagreed were discussed and a decision was reached to include/exclude each one. After the screening phase, 76 studies met the criteria for full-text assessment.

The full texts of all 76 studies were assessed by the primary researcher. The secondary researcher screened the full text for a sample of 20% and agreement was checked. At this stage there was a 93.3% agreement rate between the two reviewers. For one study, the reviewers initially disagreed, but after discussion based on the inclusion/exclusion criteria they agreed that the study should be excluded.

2.2.5 Data Collection and Items

Data collection was carried out by one reviewer (JC) who worked independently. Prior to collection, a form was designed to extract all relevant data from each included study. This form was part of a study protocol which was written by JC and reviewed by SA and AB prior to data extraction. The form included information regarding sample characteristics, objectives, study design, data collection and analysis methods, quantitative findings, conclusions, limitations and any relevant tables, figures or images. Table 3 summarises the information extracted from each article.

Information Extracted	
1	Author(s)
2	Year
3	Title
4	Country
5	Study aim(s)
6	Study design
7	Sample period
8	Sample size
9	Eye condition(s)
10	Method used to determine referral accuracy
11	Main Results
12	Limitations
13	Other important findings

Table 3: Information extracted from all studies included in the review.

2.2.6 Quality Assessment

In this review, papers which are the most relevant are focussed on, rather than papers which meet a specific standard of methodological quality. Studies were only excluded if they were considered ‘fatally flawed’, e.g. the research design was not clearly specified; however no relevant studies were deemed as such. This method has previously been described as prioritising 'signal' over 'noise' (19) and aims to maximise inclusion of relevant papers which can add valuable insights. Rather than excluding studies based on quality, they were included but critiqued during review to ensure transparency (20). When critiquing study quality, the focus was mainly on sample size for referrals, number of optometrists from which the referrals originated, number of practices from which the referrals originated, study design with respect to prospective or retrospective analysis, and the appropriateness of any statistical methods that were used.

2.2.7 Synthesis of Results

A narrative review approach was taken when synthesising the results. This method was chosen in order to provide a detailed assessment of studies reporting quantitative accuracy of optometric referrals, whilst keeping an exploratory approach. The aim was to keep the research question broad with respect to study focus variation and definitions used across the studies. The accuracy of referrals was summarised with an emphasis on referral necessity and divided the analysis into ocular conditions in order to identify any areas in which improvement in patient management is most evidently needed.

The Economic and Social Research Council developed a guidance on the conduct of narrative syntheses (21). This guidance was referred to when carrying out this review to increase transparency and trustworthiness. The framework consists of four elements:

1) Developing theory of how the intervention works, why and for whom

2) Developing a preliminary synthesis of findings of included studies

3) Exploring relationships within and between studies

4) Assessing the robustness of the synthesis

2.3 Results

2.3.1 Study Selection

Thirty-one studies were selected for analysis. The results from the search and selection process are shown in Figure 2.

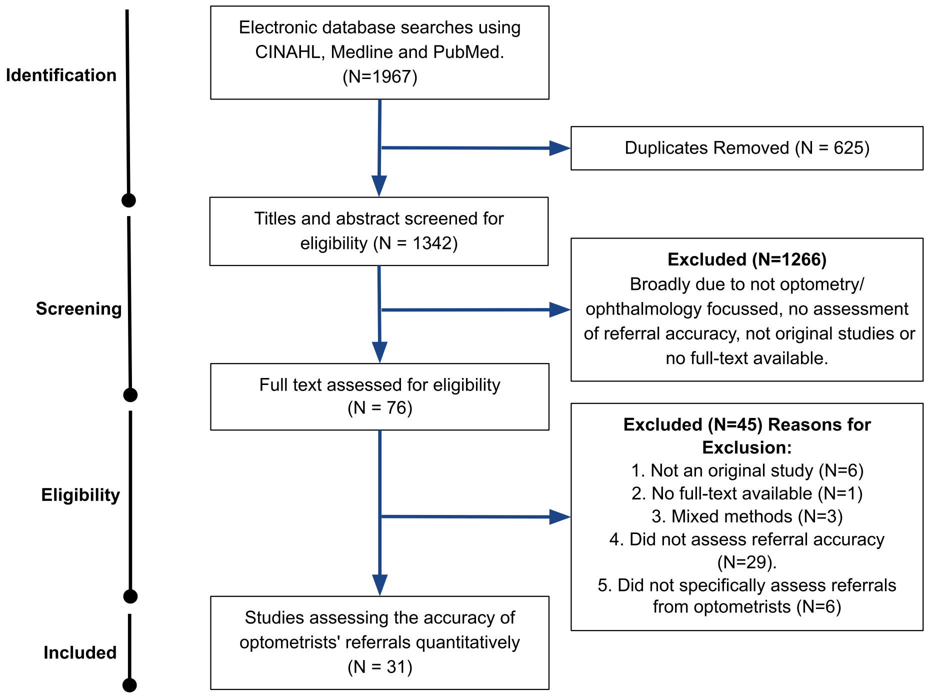

Figure 2: PRISMA flow chart detailing the selection process for the studies reviewed.

2.3.2 Study Characteristics

Of the 31 studies included in the review, 22 were retrospective analyses of referrals and clinical visits to secondary care ophthalmology, eight were prospective studies of referrals (22-29) and one study used online clinical vignettes (30). Seven studies reported results from statistical testing, with six using p-value testing for significance (15, 30-34) and one study using kappa agreement (35). Studies varied in terms of length, number of referrals, country, definition of accurate referral/true positive referral and the ocular condition(s) assessed. Details of the studies can be found in tables 4-12.

When reviewing the optometrists' referral accuracy literature, it was clear that there were several different focuses, mainly on a specific ocular condition or group of conditions. It is recognised that different ocular conditions vary in prevalence (meaning optometrists' familiarity with the condition varies), referral urgency and available treatment options, so studies were grouped based on conditions to allow a clear comparison. Other studies looked at referrals in general and/or factors that may contribute to a higher rate of inaccuracy such as referral source; these studies were also grouped based on their focus. The following sections discuss each of these groups, with some studies being allocated to more than one group. Studies which assessed referrals for multiple eye conditions are discussed first, before addressing specific eye conditions covered in the literature. The referral accuracy of optometrists is then compared with general practitioners (GPs) before lastly discussing optometrist factors which may affect their referrals.

2.3.3 General Optometric Referrals

Seven studies assessed the accuracy of referrals for all ocular conditions by optometrists and are summarised in Table 4. One study, by Cameron et al. (17) where the referrals assessed were used as a control group for a piloted new referral pathway, reported that 90% of the referrals were deemed to require ophthalmology assessment by six ophthalmology consultants retrospectively reviewing the referrals and the outcomes of the initial appointment. Four studies assessed agreement between referral diagnosis and the diagnosis given at the first visit (25, 36-38) and reported an agreement of between 67% (36) and 76% (38). Of these four studies, three also reported the true positive rate. Two of the studies defined this as the patient having an abnormality and thus not being discharged on first visit, and reported true positive rates of 93.5% (38) and 93.8% (37). The third study (36) used a different definition for a true positive whereby the ophthalmologist's decision to discharge must not have been solely influenced by clinical techniques that were not commonly available to the referring practitioner and unexpectedly reported a lower true positive rate of 71%. Two studies from the same research group (8, 39) measured referral accuracy through researchers assessing different aspects of the referrals. They reported that referrals were to an appropriate professional standard for 90-100% of referrals across 6 dyads of optometry practices paired with a hospital eye department. The referral was necessary in 90.8-97.5% of instances and was accurate in 81.1-97.5% (8, 39). It can therefore be argued from that study that optometrists in the UK perform well in the identification of cases requiring referral overall. However, that study examined dyads with good levels of communication between the optometric practice and hospital eye department and note that poorly performing optometry practices would be less likely to participate in a study which scrutinised their performance.

2.3.4 Referrals for Emergency Eye Conditions

Another important aspect of the accuracy of referrals is not just assessing whether a referral was necessary, but also whether the suggested urgency of referral was appropriate. Many patients who visit emergency eye departments have been referred by their optometrist, with this proportion having previously been reported as up to 12% of eye casualty attendances (40, 41). These referrals are important to assess as emergency departments are well-known for having long waiting times, and patients must attend an appointment either physically, or more recently remotely, in order to be triaged (42).

Four studies assessed the accuracy of referrals of emergency eye conditions from optometrists and are summarised in Table 5. For the studies that reported the percentage of 'correct' diagnoses in referrals, the optometrists' accuracy ranged from 48.2% (43) to 60% (26). The study measuring accuracy using kappa statistics (35) reported a kappa agreement across a range of different eye conditions of good (0.59) for neuro-ophthalmology to excellent (0.87) for anterior segment conditions. In one study, carried out in Canada, by McLaughlin et al. (26), 21.1% of emergency referrals from optometrists were determined to require ‘urgent’ ophthalmology attention, defined as ‘should be seen that day’. In that study, semi-urgent was defined as ‘should be seen within 1 day of referral’ (47.4%), with the remaining 31.6% patients deemed non-urgent (could be seen greater than 1 day after referral).

2.3.5 Referrals for Glaucoma

Glaucoma sub-speciality appointments are responsible for approximately a fifth of all HES workload in the UK, with an expected increase in incidence of the disease in the coming years (44). Glaucoma suspects are typically monitored over a period of time for progression at regular appointments before discharge or decision to treat, and those patients diagnosed with glaucoma require lifelong clinical follow up (45). Together, these factors create an accumulative workload for glaucoma clinics to manage, to which unnecessary referrals into the service further contribute. It is therefore important that referrals for suspected glaucoma are accurate and appropriate.

Overall, 11 studies assessed the accuracy of glaucoma referrals into secondary care ophthalmology from optometric practice and are summarised in Table 6. Ten of the studies compared optometrist referrals to the diagnosis determined by an ophthalmologist at the patient's first visit and one after at least two visits; however, the studies used different definitions for measuring the accuracy of referrals. One study by Annoh et al. (31) determined an outcome as positive based on a clinical diagnosis of primary angle closure suspect (PACS), primary angle closure (PAC) or primary angle closure glaucoma (PACG) according to the International Society of Geographical and Epidemiological Ophthalmology classification. This was the only study of the 11 to focus specifically on closed-angle glaucoma. When considering the percentage of patients discharged at first visit, studies reported a range from 16.7% (33) to 48% (46). One study by Lockwood et al. (24) reported a higher discharge value of 62.6% but this was after at least two visits. Two studies assessed the accuracy of optometrist referrals to secondary care ophthalmology pre and post new community optometry referral guidelines (33, 34). Both of these studies took place in Scotland and reported a decrease in the first visit discharge rate (FVDR) after new GOS contracts (43.2% old GOS to 16.7% new GOS, p=0.004) (33) and SIGN guidelines (29.2% pre-SIGN to 19.4% post-SIGN)(34).

One of the reviewed studies reported an unusual finding (47). The study carried out in the republic of Ireland reported that on first assessment, 67% of patients were classified as normal; however, only 35% were discharged. This finding may have been due to patients being seen within a private hospital, meaning the consultant would have more flexibility to bring patients back for another review even if considered 'normal' at their first visit. Due to its progressive nature, glaucoma can be difficult to diagnose based on one examination and the consultant may have wanted to review some patients again, especially if possessing disease risk factors. The paper focusses on the comparison of non-contact tonometry measures of IOP on referral with Goldmann applanation tonometry at the first visit. Large differences between the two IOP measures may have been another prompt to review patients again and test for fluctuations in IOP such as diurnal variations.

Table 4: Studies assessing referrals for all ocular conditions.

Study	Year	Country	Study Design	Study Period	Number of Referrals	Definition for Correct/Incorrect	Results
Evans et al.	2021	UK	Retrospective review of referrals. Three dyads of optometry practice and HES in England	May 2015-January 2018 (2 years, 7 months)	459	Researcher opinion: 1. Whether the referral was to an appropriate professional 2. Whether the referral was necessary 3. Whether the referral was accurate	Referrals to an appropriate professional 95.6-100% Referral necessary 92.9-96.7% Referral accurate 81.1-97.5%
Shah et al.	2021	UK	Retrospective review of referrals. Six dyads of optometry practice and HES in England and Scotland	May 2015-January 2018 (2 years, 7 months)	905	Researcher opinion 1: Whether the referral was to an appropriate professional 2. Whether the referral was necessary 3. Whether the referral was accurate	Referrals to an appropriate professional 90.0-100% Referral necessary 90.8-97.5% Referral accurate 81.1-97.5%
Lundmark and Luraas	2017	Norway	Prospective electronic survey	November 2014-December 2017 (3 years, 1 month)	791	Subjective assessment of the concordance of diagnostic codes and texts in referrals and medical reports, made by the two authors together.	Primary referral diagnosis matching primary medical report diagnosis 73.8% Mismatched diagnoses 21.1% Incomplete data 5.1%$ Primary referral diagnosis matching primary or secondary medical report diagnosis 79.8% Mismatched diagnoses 15.7% Incomplete data 4.6%$
Davey et al.	2016	UK	Retrospective review of referrals (sample of first 30% of new outpatient appointments each month)	December 2007-December 2008 (1 year)	366	**True positive**: Ophthalmologist confirmed condition/pathology that referrer had stated, where the ophthalmologist's decision to discharge must not have been solely influenced by clinical techniques that were not commonly available to the referring practitioner **Diagnostic agreement** : Referring Diagnosis agrees with hospital	True positive: 361 (71%) Diagnostic agreement: 244 (67%)
Fung et al.	2016	UK	Retrospective review of referrals	Backdated from 2014 (first quarter) until 1000 were reached (1991-2014)	569	**True positive:** patients not being discharged from HES with a 'normal vision' diagnosis **Diagnostic agreement**: Concordance in referred condition and diagnosed condition at HES between optometrists and ophthalmologists	True positive: 93.8% Diagnostic agreement: 76.1%
Pierscionek et al.	2009	UK	Retrospective review of referrals	January-March 2007 (3 months)	323	**True positive**: Patient diagnosed as anything other than 'no abnormality detected by ophthalmologist' **Diagnostic agreement**: Referral diagnosis compared to final diagnosis made by ophthalmologist	True positive: 302 (93.5%) Diagnostic agreement: 225 (69.7%)
Cameron et al.	2009	UK	Retrospective review of referrals	January–June 2005 (6 months)	112	Vetted by six ophthalmologist consultants to classify which referrals required a HES appointment.	Required a HES appointment 95 (85%) Did not require HES appointment 11 (10%) GP did not refer onward 6 (5%)

Table 5: Studies Assessing referrals for emergency eye conditions.

Study	Year	Country	Study Design	Study Period	Number of Referrals	Definition for Correct/Incorrect	Results
Mas-Tur et al.	2021	UK	Retrospective review of referrals	April 2016-September 2016	1059	Agreement with the assessment by an ophthalmologist but not reliant on equipment available to them	Diagnostic agreement (kappa): Anterior segment 0.87 Vitreo-retinal 0.68 Medical retina 0.66 Neuro-ophthalmology 0.59 Glaucoma 0.64 Lids 0.66 **Discharged at first visit (54%)**
McLaughlin et al.	2018	Canada	Prospective case review	April 1st, 2016- September 1st, 2016 (6 months)	57	Alangh's criteria for agreement of diagnosis through categorization of the provisional diagnosis based on location of pathology. Ophthalmologist also determined the urgency of review required.	Diagnostic agreement: 30/50 (60%) 7 not yet diagnosed Urgency of review required: Urgent 12 (21.1%) Semi-urgent 27 (47.4%) Non-urgent 18 (31.6%)
Nari et al.	2017	Canada	Retrospective review of referrals	January 17th, 2011 to July 17th, 2011 (6 months)	309	Agreement with the final diagnosis.	Diagnostic agreement: Correct 166 (54%) Incorrect 111 (36%) Non-specific 18 (6%) Not yet diagnosed 12 (4%)
Jackson	2009	Australia	Retrospective review of referrals from two hospitals	Alexandra Hospital 18th April - 25th October 2006 (6 months 7 days) Royal Brisbane and Women's Hospital 1st July -30th September 2006 (3 months)	114	Agreement with the diagnosis made in the ophthalmology department	Diagnostic agreement: 55 (48.2%)

Table 6: Studies assessing referrals for glaucoma

Study	Year	Country	Study Design	Study Period	Type of Glaucoma	Number of Referrals	Definition for Correct/Incorrect	Correct
Huang et al.	2020	Australia	Prospective review of referrals (control arm)	March 2015-June 2018	All glaucoma referrals	74	Number of referrals resulting in treatment initiation or monitoring on first assessment at the HES	Treatment initiated 25 (33.8%) Monitoring 30 (40.5%) **Discharged at first visit 19 (25.7%)**
Sii et al.	2019	UK	Retrospective review of referrals pre and post SIGN guidelines	October – November 2014 and September - October 2016	All glaucoma referrals	Pre-SIGN 312 Post SIGN 325	First visit discharge rate (FVDR)	First visit discharge pre-SIGN 91 (29.2%) First visit discharge post-SIGN 63 (19.4%)
Kamel et al.	2019	Republic of Ireland	Retrospective review of referrals and first clinic appointment	January 2007 - June 2009 (2 years and 6 months)	All glaucoma referrals	98	Compared to the diagnosis given to each patient during their first assessment at a private eye hospital	Confirmed glaucoma 7 (7%) Glaucoma suspect 14 (14%) Ocular hypertension 11 (11%) **Normal 66 (67%)** **Discharged at first visit 35 (35%)**
Annoh et al.	2019	UK	Retrospective review of referrals and first clinic appointment	June-November 2016 (6 months)	Open-angle and asymptomatic closed angle	715 (95 indicated to have suspect narrow angles)	Clinical diagnosis of PACS PAC or PACG according to the International Society of Geographical and Epidemiological Ophthalmology classification	False-positive 36/95 (37.9%) False-negative 19/715 (3.1%) Discharged at first visit (suspect narrow angles referrals) = 11/95 (12%) Discharged at first visit (overall) 156/715 (25%)
Founti et al.	2018	UK	Multicentre, prospective, observational, cross-sectional study (however only in the UK site were there any patients referred by optometrists)	May 2013-March2014 (10 months)	All glaucoma referrals	28	An outcome was defined as positive when the management plan was an intervention or active monitoring and as negative when the management plan was same-day discharge.	Positive 16 (57.1%, CI 24.6-63%) Negative with same day discharge 12 (42.9%, CI 38.8-75.4%)
Khan et al.	2012	UK	Retrospective review of referrals and first clinic appointment	January 2011 - ? (6-week period)	All glaucoma referrals	102	Compared to the diagnosis given to each patient on their first assessment at the HES.	Confirmed glaucoma 17 (17.6%) Glaucoma suspect 18 (17.6%) Ocular hypertension 24 (23.5%) Narrow angles requiring PI 12 (11.8%) **No glaucoma or OHT 30 (29%)** **Discharged at first visit 31 (30%)**
Lockwood et al.	2010	UK	Prospective assessment of referrals and clinic appointments	6 months	All glaucoma referrals	441	Compared to the diagnosis given to each patient on their first assessment at the HES.	Chronic open angle glaucoma 33 (7.5%) Glaucoma suspect 92 (20.9%) OHT 49 (11.1%) Angle closure glaucoma 8 (1.8%) Pigment dispersion syndrome 1 (0.2%) Trauma 1 (0.2%) **Normal 257 (58.3%)** **Discharged after at least two visits 276 (62.6%)**

Ang et al.	2009	UK	Retrospective review of referrals pre and post new GOS contracts	June- November 2005 and June- November 2006	All glaucoma referrals	Old GOS 183 New GOS 120	A true positive was defined as a referral that was found to have definite glaucomatous damage	True positives old GOS 33 (18.3%) True positives new GOS 38 (31.7%) Discharged at first visit old GOS 79 (43.2%) Discharged at first visit new GOS 20 (16.7%)
Salmon et al.	2007	UK	Retrospective review of referrals and first clinic appointment	2003-2005 (3 years)	All glaucoma referrals	1106	Compared to the diagnosis given to each patient on their first assessment at the HES.	No glaucoma or OHT and discharged at first visit 531 (48%)
Bowling et al.	2005	UK	Retrospective review of referrals and first clinic appointment	July 1994 - June 2004 (10 years)	All glaucoma referrals	2506	Compared to the diagnosis given to each patient on their first assessment at the HES.	Confirmed glaucoma 511 (20%) Glaucoma suspect 125 (5%) OHT 747 (30%) **No glaucoma or OHT 1123 (45%)** **Discharged at first visit 1148 (45.3%)**
Theodossiades et al.	2004	UK	Prospective review of referrals (control arm)	June 2000- January 2001 (7 months)	All glaucoma referrals	119	Positive predictive value defined as a confirmed or suspected diagnosis of glaucoma, where 'glaucoma' encompasses open angle, closed angle and secondary glaucoma.	Positive predictive value 55/119 (46.2%)

2.3.6 Referrals for Cataract

Cataract referrals make up the largest proportion of referrals from primary care to secondary care in the UK (36-38). Investigating the accuracy of these referrals is essential to explore the potential strain that these initial numbers put on secondary care ophthalmology . However, the method of assessing the accuracy of cataract referrals is different to other common ocular conditions as referrals should only be made to initiate listing for surgery. Thus, the seven studies evaluated in this review assessed accuracy of referrals from optometrists based on whether patients had been listed for surgery and are summarised in Table 7. The listing rate ranged from 47% (48) to 81% (37) for referrals overall, with a very recent study from the west of Ireland reporting a value somewhere in-between (68.5%)(49). Two studies separated cataract referrals into the method of referral (23, 36). In both studies, the listing rate increased when a direct referral from optometrist to secondary care ophthalmology was made to between 83% (23) and 100% (36). In both studies, the lowest listing rates came from referrals that used the General Ophthalmic Services (GOS) 18 forms. For Lash et al's study, this rate was 73%. For Davey et al's study this listing rate was 63% for 'new' GOS18 forms and 72% for 'old' GOS18 forms.

2.3.7 Referrals for Neovascular AMD

Only one paper focussed on optometric referrals for neovascular AMD (Table 8). This study, carried out in the UK, used a prospective study design over a 21 month period to evaluate the optometric referrals, specifically for neovascular macular degeneration, using a rapid access referral form (28). This study assessed 54 referrals and found that only 20 (37%) were confirmed as having neovascular AMD. Additionally, this study assessed agreement of optometrist referrals with an ophthalmologist with respect to the specific clinical signs reported on referral. The agreement for retinal haemorrhage was 83.3%, for exudates 66.7%, for drusen 51.9% and for subretinal fluid 44.4%. The most common conditions that the optometrists had misdiagnosed as neovascular AMD were dry AMD (18.5%), Epi-retinal membrane (9.3%), branch retinal vein occlusion (7.4%) and central serous chorioretinopathy (7.4%).

2.3.8 Paediatric Referrals

Optometrists play an important role in the screening of children for reduced vision and possible binocular vision abnormalities and optometry paediatric screening in the UK may be preferred over visiting a GP practice, due to the limited speciality knowledge of GPs (50). Only one study assessed the accuracy of optometrists' referrals of paediatric patients (Table 9) (32). This retrospective analysis was mainly focussed on the accuracy of GP referrals but also reported separately the accuracy of referrals initiated by optometrists. This study of 45 optometrist referrals for children with suspect BV abnormalities, found that 88.9% of referrals either fully or partially matched the diagnosis made by an ophthalmologist in the HES. The accuracy of diagnosis also increased with patient age, with 0% (n=1) accuracy for patients 0-2 years old, 87% (n=23) accuracy for patients 3-6 years old and 90% (n=21) accuracy for patents 7-13 years old. However, the link between age and referral accuracy was not statistically significant (p=0.06).

Table 7: Studies assessing referrals for cataract

Study	Year	Country	Study Design	Study Period	Number of Referrals	Measure of Accuracy	Results
Canning et al.	2022	Ireland	Retrospective audit of referrals	February 2021-February 2022 (1 year)	167	Listed for surgery after assessment by consultant ophthalmologist	114 (68.5%)
Do et al.	2018	Australia	Retrospective audit of referral letters	August-September 2014 (2 months)	76	Listed for surgery/ surgery performed 12-15 months post-referral	38 (50%)
Fung et al.	2016	UK	Retrospective review of referrals	Backdated from 2014 (first quarter) until 1000 was reached (1991-2014)	26	Listed for surgery	21 (81%)
Davey et al.	2011	UK	Retrospective audit of referral letters (Random sample)	2007-2008 (1 year)	Overall 61 Cataract CHOICE 8 Old GOS18 32 New GOS18 16 Letter 5	Listed for surgery	**Overall, 45 (73.8%)** Cataract CHOICE 8 (100%) Old GOS18 23 (72%) New GOS18 10 (63%) Letter 4 (80%)
Tattersall and Sullivan	2008	UK	Retrospective audit of referral letters	August 2005 (2 weeks)	30	Clinical outcome after assessment by consultant ophthalmologist	23 (76.7%)
Lash et al.	2006	UK	Prospective audit of referral letters	4th October- 6th December 2004 (2 months)	351 Overall 162 GOS 18 143 Direct 46 Letters	Listed for surgery after assessment by consultant ophthalmologist	**Overall, 272 (78%)** Direct referral (83%) Referral letter (78%) GOS 18 (73%)
Lash	2003	UK	Retrospective review of referrals	12 February to 23 April 2001	163	Listed for surgery	77 (47%)

Table 8: Study assessing referrals for neovascular AMD

Study	Year	Country	Study Design	Study Period	Number of Optometrist Referrals	Definition of Accuracy	Accuracy
Muen and Hewick	2011	UK	Prospective study of all optometry referrals using a rapid access referral form	December 2006-August 2009 (21 months)	54	Diagnosed with neovascular AMD by an ophthalmologist	20 (37%)

Table 9: Study assessing referrals for paediatric binocular vision

Study	Year	Country	Study Design	Study Period	Number of Optometrist Referrals	Definition of Accuracy	Accuracy
Waters et al.	2021	UK	Retrospective review of all referrals	March 2013- November 2017 (4 years, 9 months)	45	Condition confirmed during hospital consultation (match or partial match)	40 (88.9%)

2.3.9 Comparison of Optometrists with GP

Assessing the accuracy of referrals between optometrists and GPs is important to determine whether these practitioners manage specific eye conditions more appropriately. Seven studies assessed the accuracy of optometrist referrals in comparison to GPs Table 10). Of these, three assessed the accuracy of referrals for all eye conditions (36-38). All three reported higher diagnostic accuracy for optometrists (67% vs 56%, 69.7% vs 65.8% and 76.1% vs 67.2%). When assessing the true positive rate, two studies (37, 38) reported a higher rate for optometrists when defining a true positive as a referral whereby an abnormality was present, even if the referral findings/diagnosis did not match the HES report (93.5% vs 92.6% and 93.8% vs 92.3%). The third study (36) reported a higher true positive rate for GPs (96% vs 71%), but used a different definition for a true positive whereby the ophthalmologist's decision to discharge must not have been solely influenced by clinical techniques that were not commonly available to the type referring practitioner. These commonly available techniques were not defined so it was unclear how much they differed between practitioners. Two studies assessed the accuracy of referrals for acute eye conditions (43, 51). Both studies reported a higher accuracy of optometrist referrals (48.2% and 54%) compared to GP referrals (35.9% and 33%). One study assessed the accuracy of referrals for paediatric binocular vision (BV) conditions (32). This study defined an accurate referral as a full or partial match to the diagnosis made at first visit to the HES, where a partial match was not clearly defined, and reported a significantly higher accuracy of optometrist referrals (88.9%) compared to GP referrals (65%) (p=0.01). One study by Founti et al. (22) assessed the accuracy of referrals for suspected glaucoma and reported a higher accuracy of referral for optometrists, defined as a positive outcome when the management plan was an intervention or active monitoring. Optometrist referrals were positive for 57.1% compared to 50% of GP referrals. However, this study assessed a very small number of referrals, with only two referrals coming from GPs.

Table 11 represents a summary of the accuracy of referrals from optometrists and GPs reported when using agreement with an ophthalmologist at the HES appointment as the measure of accuracy. A weighted average accuracy was calculated for both optometrists and GPs by accounting for the sample size used in each study: i.e., the reported percentage accuracy was multiplied by the sample size for each study before adding those results together. The total was then divided by the total sample size of all of the six studies. Overall, optometrists had an accuracy rate which was 18.6% higher than GPs for diagnostic agreement.

2.3.10 Optometrist factors affecting the accuracy of referrals

To work towards improving the accuracy of optometrist referrals, it is important to assess the factors which may be influencing referral decisions. Two studies, both carried out in the UK, assessed the optometrist factors that may influence the accuracy of referrals (Table 12). One of the studies was an online vignette study, whereby optometrists indicated their management decision and reason for the decision (30). This study assessed years of clinical experience and continuing education and training (CET) points completed over six months as factors and reported no correlation between change in score and CET points over the six months ($r=0.17$, $p=0.37$); there was no correlation between the change in score and the number of peer discussion sessions undertaken ($r=0.24$, $p=0.90$). However, the type of CET training undertaken was not standardised. There was significant negative correlation between the number of referrals made by practitioners and their time since qualification ($r_s=0.39, p=0.005$). However, although initiating more false-positive referrals, it is unclear how level of experience may affect false-negative referrals. The clinical vignette study (30) reported that 3 participants with over 20 years' experience only referred 5 cases despite 6 being chosen as certain referrals in the study design. In comparison, the 7 participants that referred ≥10 cases all had at most 4 years of experience. Eight cases were chosen as 'grey area' cases where there was no definite correct answer, so although less experienced practitioners referred more cases, it was not clear whether that meant they were incorrect. The second study was a retrospective review of referrals into the HES (36). They reported that female optometrists made significantly more false-positive referrals than males (39% vs 23%, $p=0.008$) and this significant difference was still present when years since registration was controlled for. The proportion of false positives decreased by 6.2% per year since registration ($p<0.001$). There was a significantly higher proportion of false-positive referrals from multiple practices compared to independent practices ($p=0.005$) but this value became insignificant when controlling for years since registration ($p=0.20$). The proportion of false-positive referrals also had a significant link to the type of condition referred ($p=0.046$), with referrals for lids/lashes being the most accurate and referrals for visual disturbance/other being the least accurate.

Table 10 Studies comparing referral accuracy of optometrists and GPs

Study	Year	Country	Study Design	Study Period	Condition(s)	Number of Optometrist Referrals	Number of GP Referrals	Definition of Accuracy	Accuracy Optometrists	Accuracy GPs
Waters et al.	2021	UK	Retrospective review of all referrals	March 2013- November 2017 (4 years, 9 months)	Paediatric BV	45	54	Condition confirmed during hospital consultation (match or partial match)	40 (88.9%)	35 (65%)
Founti et al.	2018	UK	Multicentre, prospective, observational, study	May 2013-March2014 (10 months)	All glaucoma referrals	28	2	An outcome was defined as positive when the management plan was an intervention or active monitoring and as negative when the management plan was same-day discharge.	Positive 16 (57.1%, CI 24.6-63%) Negative with same day discharge 12 (42.9%, CI 38.8-75.4%)	Positive 1 (50%, CI 0-100%) Negative with same day discharge 1 (50%, CI 0-100%)
Nari et al.	2017	Canada	Retrospective review of referrals	January 17th, 2011 to July 17th, 2011 (6 months)	Acute eye disease	309	102	Agreement with the final diagnosis.	Correct 166 (54%) Incorrect 111 (36%) Non-specific 18 (6%) Not yet diagnosed 12 (4%) Baseline 1 (<1%)	Correct 34 (33%) Incorrect 33 (32%) Non-specific 27 (26%) Not yet diagnosed 4 (4%) Baseline 45 (4%)
Davey et al.	2016	UK	Retrospective review of referrals)	December 2007- December 2008 (1 year)	All ocular conditions	392 366 qualified 26 pre-registration	131	**True positives:** Ophthalmologist confirmed condition/pathology. Discharge was not solely influenced by clinical techniques that were not currently commonly available to the referring practitioner **Diagnostic agreement** : Referring Diagnosis agrees with hospital	True positive: 361 (71%) Diagnostic agreement: 244 (67%)	True positive: 127 (97%) Diagnostic agreement: 73 (56%)
Fung et al.	2016	UK	Retrospective review of referrals	Backdated from 2014 (first quarter) until 1000 were reached (1991-2014)	All ocular conditions	569	143	**True positive:** patients not being discharged from HES with a 'normal vision' diagnosis **Diagnostic agreement:** Concordance in referred condition and diagnosed condition at HES between optometrists and ophthalmologists	True positive: 93.8% Diagnostic agreement: 76.1%	True positive: 92.3% Diagnostic agreement: 67.2%
Jackson	2009	Australia	Retrospective review of referrals from two hospitals	**Alexandra Hospital** 18th April - 25th October 2006 (6 months 7 days) **Royal Brisbane and Women's Hospital** 1st July -30th September 2006 (3 months)	Acute eye disease	114	535	Agreement with the diagnosis made in the ophthalmology department	55/114 (48.2%)	192/535 (35.9%)
Pierscionek et al.	2009	UK	Retrospective review of referrals	January-March 2007 (3 months)	All ocular conditions	323	243	**True positive:** Patient diagnosed as anything other than 'no abnormality detected by ophthalmologist' **Diagnostic agreement**: Referral diagnosis compared to final diagnosis made by ophthalmologist	True positive: 302 (93.5%) Diagnostic agreement: 225 (69.7%)	True positive: 225 (92.6%) Diagnostic agreement: 160 (65.8%)

Table 11: Comparison of diagnostic agreement accuracy for Optometrists vs GPs

Study	Agreement Optometrists	Agreement GPs	Difference
Waters et al.	88.9%	65%	23.9%
Davey et al.	67%	56%	11%
Pierscionek et al.	69.7%	65.8%	3.9%
Fung et al.	76.1%	67.2%	8.9%
Jackson	48.2%	35.9%	12.3%
Nari et al.	54%	33%	22%
Weighted Average	**67.5%**	**48.9%**	**18.6%**

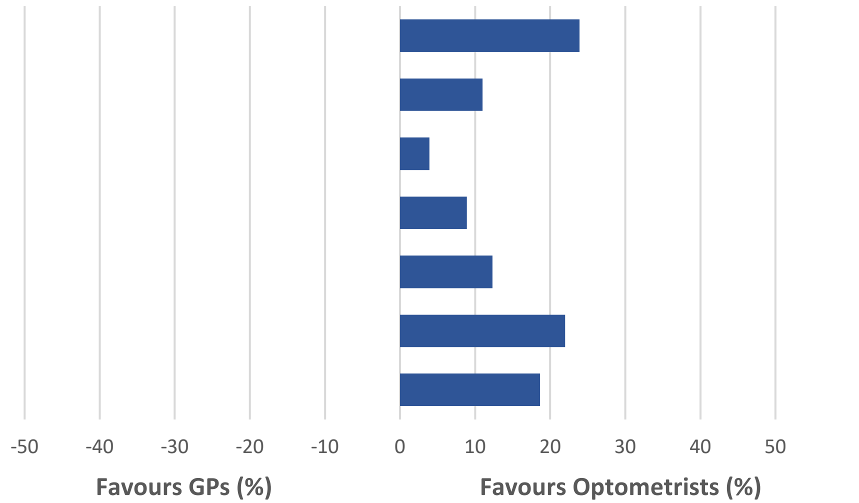

Table 12: Studies assessing the factors affecting false-positive referral rates

Study	Year	Country	Study Design	Study Period	Number of Optometrists /Referrals	Factors Assessed	Definition of Accuracy	Accuracy	Factors
Parkins et al.	2018	UK	Online vignettes	6 months	**60 Optometrists** 31 Qualified 18 Newly qualified 11 Pre-registration	1. Years of Experience 2. CET training over 6 months	For each clinical vignette, Optometrists indicated what tests they would perform, their management decision, reason for decision and additional questions. Scoring was determined by an expert panel and participants' performance was compared to an expert.	-	No correlation between change in score and CET points over the 6 months (r=0.17, p=0.37) No correlation between the change in score and the number of peer discussion sessions undertaken (r=0.24, p=0.90) Significant negative correlation between the number of referrals made by each practitioner and their time since qualification (rs=0.39,p=0.005).
Davey et al.	2016	UK	Retrospective review of referrals	December 2007-December 2008 (12 months)	366 referrals made by qualified optometrists	1. Gender 2. Type of practice (multiple vs independent) 3. Years since professional registration 4. Condition	**False-positive referral**: Ophthalmologist discharged the patient due to the absence of significant ocular pathology. OR Ophthalmologist diagnosed the patient with, or was suspicious of, pathology that was unrelated to the diagnosis given or implied by the optometrist. Decisions were not influenced solely by clinical techniques that were not currently commonly available to the optometrist.	Optometrist (n = 366) 105 (29%) Female optometrists (n = 122) 47 (39%) Male optometrists (n = 159) 36 (23%) Multiple optical practice (n = 206) 74 (36%) Independent optical practice (n = 169) 38 (22%) Females in multiple practice (n = 82) 36 (44%) Females in independent practice (n = 40) 11 (28%) Males in multiple practice (n = 68) 21 (31%) Males in independent practice (n = 91) 15 (16%)	**Females vs Males** (p=0.008) Controlled for years since registration (p=0.029) Controlled for years since registration and practice type (p=0.073) **Independent vs multiple** (p=0.005) Controlled for years since registration (p=0.20) Controlled for gender and years since registration (p = 0.38) **Condition** (p=0.046) (least to most FPs) 1. lens, 2. lids, lashes, 3. glaucoma, 4. everything else, 5. visual disturbance/other Proportion of FPs decreases by 6.2% per year since qualification (p<0.001)

2.4 Discussion

In this section, the main findings from the reviewed studies and their possible implications are discussed, based on four core themes:

1. Condition-based referral accuracy
2. Optometrist factors affecting referral accuracy
3. Missing information in the literature
4. Enhanced referral schemes

The first two themes were identified through comparing the methodology and outcomes across all the reviewed studies and link directly to the objectives of the review. The third and fourth themes were identified based on knowledge of current practice independent of the studies meeting the inclusion criteria for this review. The third theme was specifically shaped by information expected to have been included in the literature. These four themes are discussed separately, with some also containing sub-themes.

2.4.1 Condition-based Referral Accuracy

It was evident from the review that there is variability in the accuracy of referrals depending on the type of eye condition(s) being referred, with one study by Davey et al. (36) that compared the accuracy of all referrals based on condition reporting a significant effect of condition group on the level of false-positives ($p=0.046$) . Overall, from the review, optometrists' referral accuracy based on the diagnostic agreement with specialists in secondary care ophthalmology varied across eye conditions. This variation is not surprising, as the frequency with which different conditions are encountered in primary care varies, meaning optometrists may feel more confident in their examination of commonly encountered conditions such as cataract compared to, for example, suspected neuro-ophthalmological disease. Additionally, the risk to the patient of delaying intervention for different conditions varies. Using the same examples, delaying the identification and treatment of a neuro-ophthalmological condition would typically pose a much higher risk to the patient’s sight/life than a cataract. Of note, the range for the accuracy of referrals for suspected emergency ocular conditions as a whole was lower than for other conditions that were covered in detail, with only 21.1% of emergency referrals considered to require urgent attention in one study (26). This may indicate that optometrists are erring on the side of caution for conditions they consider potentially urgent. However, it also highlights ambiguity in the terms used to describe different referral urgencies. In that study, ‘semi-urgent’ was defined as still needing to be seen within one day of referral. In comparison, the College of Optometrists ‘Urgency of Referrals’ guidelines define this same timeframe as an ‘emergency’ (52). Thus, the proportion of referrals appropriately directed to an emergency department rather than via a routine pathway appears higher than the 21.1% which were determined to be ‘urgent’. In that same study, the vague definition for ‘nonurgent’ (could be seen greater than one day after referral) also meant that referrals requiring review from a range of two days post-referral up to a routine referral timeline such as three months or longer could be classed as ‘nonurgent’.

As the accuracy for conditions such as neovascular AMD and paediatric BV were only addressed by one study in the review, it was difficult to draw conclusions for these conditions. It is somewhat surprising that the literature search found only one study focusing on the accuracy of referrals for age-related macular degeneration (AMD), considering that AMD is the most frequent cause of visual impairment in developed countries and that distinguishing the 'wet' form from the 'dry' form is essential for determining which patients require treatment.

The difference in referral accuracy across ocular conditions also makes it difficult to draw conclusions from the studies comparing the accuracy of referrals from GPs and optometrists as the practitioners largely refer different eye conditions. One of the reviewed studies reported that 40% of GP referrals were for disorders of the lacrimal system, eyelids and orbit, whereas referrals for the same group of conditions made up less than 5% of optometrist referrals (37). In comparison, the most referred condition from optometrists was disorders of the lens, which made up 20% of optometrist referrals but only around 7% of GP referrals. This difference in referral patterns suggests that patients report more commonly to GPs for conditions of the lids/lashes and lacrimal system. However, it may also suggest that GPs are more comfortable referring these conditions themselves but may send patients to optometrists for assessment of other suspected ocular abnormalities, perhaps due to the lack of available ophthalmic techniques and specialised training in general practice.

2.4.2 Referrals for Cataracts

One condition encountered frequently in primary care practice is cataracts, which are typically easily identified during an ocular health check. The referral accuracy for cataracts was covered in detail by the studies reviewed. As cataracts are most commonly age-related and slowly progressing, they should be monitored in primary care until a referral is necessary to initiate listing for surgery. Thus, the studies evaluated in this review assessed accuracy of referrals from optometrists based on whether the patients had been listed for surgery, as a surrogate measure for whether a referral was appropriate. Although optometrists are competent in identifying cataracts on examination and reported referral accuracy was reasonable, the fact that listing rates were not nearing 100% for typical referral routes means many patients are being referred before surgery is indicated. The 'Action on Cataracts' government guidance in the UK (53) stated that cataract referrals should be based on reduced visual acuity, impaired lifestyle and the willingness of the patient to have surgery, in order to avoid unnecessary referrals. In the studies carried out in the UK, it was reported that the main reason for patients not being listed for surgery was due to them not being symptomatic of their cataracts (23, 54). These findings suggest that a number of patients who are not yet symptomatic of their cataracts are being referred unnecessarily perhaps due to optometrists either not asking the correct symptoms and lifestyle questions prior to referral or that optometrists' thresholds with respect to symptoms requiring surgery is lower than that of the ophthalmologists. This interpretation, of course, would require further assessment.

2.4.3 Referrals for Glaucoma

Another condition covered in detail by the reviewed studies was suspected glaucoma. Although encountered in primary care more often than rarer optic neuropathies such as optic neuritis, it is still seen infrequently in primary care practice. The sub-optimal referral accuracy reported is not surprising, as glaucoma diagnosis and detection can be very tricky, particularly in early stages of disease and partly due to its characteristically progressive nature. As previously mentioned, it is also rare for optometrists to receive feedback about the outcomes from their referrals, making it difficult to learn from previous patient encounters.

Normal physiological variations in optic nerve morphology can make the identification of a glaucomatous optic nerve difficult and visual field testing and IOP measurements can be variable, with repeated testing advised for many cases where abnormal results are found. Best practice for optic disc evaluation would be a stereoscopic view through a dilated pupil, but it may be impractical for optometrists working in busy practice to perform dilation on all glaucoma suspects. Optometrists practising in the UK have previously reported that they were constrained by time and are required to see a patient every 20-30 minutes (55). This means that additional tests such as repeated visual fields, Goldmann tonometry and/or dilated fundus exam would be virtually impossible in the time available.

Although the College of Optometrists clinical management guidelines provide clear advice for the referral of a range of suspect ocular conditions; for glaucoma, specific guidelines in relation to a risk assessment based on clinical findings and patient history are lacking in England. The results from the reviewed studies carried out in Scotland suggest that a change in primary care guidelines, specific to Scotland, has improved the accuracy of glaucoma referrals. From 2006 a new GOS contract for NHS eye tests by community optometrists was implemented which aimed to reduce unnecessary referrals for glaucoma through introducing supplementary examinations. Additionally, since the 2006 GOS contract, there was a consensus that specific referral guidelines should be set out (56) which led to the introduction of the Scottish Intercollegiate Guidelines Network (SIGN) guideline 144 in March 2015 (57). Results from the reviewed studies have suggested a positive impact of both the GOS contract (33) and the new SIGN guidelines (34), suggesting that similar guidelines, if implemented in other countries/regions may aid optometrists in making better referral decisions.

Particularly for the reviewed studies assessing glaucoma referrals, the time periods from which the referral samples were assessed must also be considered. This consideration is important because referral guidelines in the UK have changed during the past 20 years. In December 2009, the College of Optometrists released guidelines which advised optometrists to refer patients with a measure of intraocular pressure of more than 21 mmHg, even in the presence of normal optic disc and visual fields, stating that practitioners could leave themselves ‘legally exposed’ if they failed to do so. This guidance may explain why two studies carried out in 2010 and

2011 (24, 58) both found that when referral was based on one measure alone, intra-ocular pressure (IOP) was the most common, with this being the case in 44% (24) and 43% of patients (58). These findings contradicted an earlier study carried out prior to the 2009 guidelines (46) which reported that 65.5-74.3% of referrals were made based on optic disc appearance alone. It must also be noted that the NICE and College of Optometrists guidelines again changed in 2017 and recommended that referral based only on IOP should be when IOP is 24mmHg or more using Goldmann-type applanation tonometry; none of the studies identified in this review used samples taken after this new guidance was published. Since its introduction, the number of referrals based on IOP findings alone as well as the proportion of false-positive glaucoma referrals may have reduced, due to an increase in the IOP threshold guidance for referral.

2.4.4 Definitions for Referral Accuracy

As well as there being a range in referral accuracy between conditions, there was also variability between studies reporting the referral accuracy for the same condition. When reviewing the studies, it was evident that there was significant variation in the classifications used when determining whether a referral from primary care optometrists was accurate. This heterogeneity in classification criteria created some difficulty when interpreting and comparing the results reported and appeared to be a contributing factor to why differences in referral accuracy within the same eye condition were reported. One approach used by many of the studies was to assess whether optometrists' referral diagnosis agreed with the ophthalmological diagnosis. Comparing the diagnosis made by an optometrist in primary care with that of an ophthalmologist can be problematic as optometrists are generally more limited with respect to the equipment and diagnostic aids available to them. Additionally, many optometrists carry out sight tests alone, in busy clinics, without access to specialist opinion, and often rely on their individual clinical judgement to decide on a most likely diagnosis and management decision. Primary care optometrists can therefore be considered overall as more ‘generalist’ in their knowledge and experience. In comparison, clinicians working in secondary care ophthalmology tend to be more specialised, often receiving additional training and having significantly more experience with specific eye conditions. They often have advanced diagnostic techniques available to them and other specialists to ask for advice or opinions on complex clinical cases.

It can therefore be argued that a more appropriate assessment of the accuracy of referrals is to determine whether a referred patient required an ophthalmology assessment or not, regardless of whether the referral diagnosis matched the diagnosis made during the ophthalmology appointment. This method of assessing referral accuracy specifically focusses on the rate of 'false-positive' referrals made and was used by a number of reviewed studies by identifying which patients required onward referral and could not be safely managed in primary care. The General Optical Council (GOC) standards of practice guidelines state that optometrists should "recognise and work within the limits of your scope of practice" and "be able to identify when you need to refer a patient in the interests of the patient’s health and safety, and make appropriate referrals" (16); thus, optometrists should refer any condition that they feel unable to manage in practice. One may argue that tentative diagnoses do not need to be completely accurate, but that the referral needs to be appropriate.

One could also argue that in order to fully evaluate the accuracy of referrals, the false-negative rate should also be assessed. This measure would identify the number of referrals which require ophthalmology review but were not referred by optometrists. Only one study reported a false-negative referral rate, and focussed specifically on narrow anterior chamber angle identification (31), with their population consisting only of patients referred for suspected glaucoma which is not representative of all patients tested in primary care. Other studies outside this review have also successfully assessed the false-negative referrals generated within referral triage pathways such as glaucoma referral refinement (59-61), and assessed false-negatives within management decisions made as part of the COVID urgent eye care scheme (62). It can be recognised that false-negative referral rate from eye examinations performed in routine primary eye care practice would be difficult to measure, as it would require a secondary assessment of unreferred patients and is unlikely to be feasible; however, it is important to consider as a shortcoming of the reviewed studies.

2.4.5 Optometrist Factors

The reviewed studies identified several factors which may contribute to the accuracy of referrals made by optometrists. Firstly, it is not surprising that for both studies assessing optometrist factors, a shorter time since qualification had a significant negative effect on the number of referrals made and referral accuracy (30, 36). Although significantly more false-positive referrals were made from multiple practices compared to independent practices (36), this appeared to be explained by multiple practices employing optometrists with fewer years of experience. In the early stages since qualification, optometrists are likely to be more cautious with their clinical decision-making, especially when assessing eye conditions that they are not familiar with. Through gaining experience and learning from previous patient encounters, optometrists are likely to become more confident with their clinical assessment and ability to manage patients in primary care.

In a retrospective study (36), the results also suggest that female optometrists were significantly more likely to make false-positive referrals compared to male optometrists, which remained the case when years since registration was controlled for. The authors suggest that this finding may be explained by 'years since registration' as a measure of experience not being an accurate representation of clinical experience, particularly for females. Females are more likely to take career breaks for maternity leave or to work part-time due to care commitments (63), and these interruptions can affect continuity of practice and training. However, previous studies into other clinicians, such as GPs, have also found evidence of differences in clinical decision making between males and females. One study by Boulis et al. (64) found that female primary care physicians were more likely to refer patients and other studies have reported more aggressive disease screening in patients of female physicians, irrespective of the patient's gender (65, 66). Although recent studies are lacking, these may indicate a more cautious management approach by females which could lead to a higher number of false-positive referrals. Again however, there was no available measure of false-negative cases and gender as a factor was reported by one study only.

2.4.6 Missing Information in the Literature

Another theme formed from the analysis was that the literature was lacking in certain topics and/or backgrounds. Of note, 23 of the 31 studies reviewed were carried out in the UK. This means that the findings apply primarily to UK optometry practice. A smaller number of studies were carried out in Canada (n=2), Australia (n=3), Norway (n=1) and the republic of Ireland (n=2), but there was overall little diversity. This lack of diversity is likely to be due partly to the inclusion criteria excluding studies that were not published in English; however, it may also be due to large differences in eyecare systems across the world, with optometrists playing varied roles in countries with different scopes of practice. Even within the UK, eyecare pathways and local guidelines can differ considerably between regions. Thus, it is recognised that results from the reviewed studies may not accurately represent the accuracy of referrals internationally or in the UK overall and may be specific to the regions in which they were carried out.

2.4.7 No Focus on Ocular Imaging

Another topic that was lacking in the reviewed literature was an examination of advanced ocular imaging, such as OCT imaging, and how its use may have affected the referrals being made from primary to secondary care. In recent years, there has been a dramatic increase in the use of advanced ocular imaging in UK primary care (11). One might expect that the introduction of OCT scanning has increased the rate of false-positive referrals for suspected retinal disease. This expectation may arise because the detailed visualisation of retinal layers provided by OCT devices may identify benign changes in asymptomatic patients that appear as abnormalities and would otherwise be undetected. Conversely, the increased clinical information presented by OCT imaging is likely to have improved optometrists' ability to detect subtle pathological features such as retinal fluid, and thus detect more cases of conditions requiring urgent referral such as choroidal neovascularisation.

A pilot study by Kern et al (67), where primary care optometrists referred patients via a web-based interface with retinal and OCT imaging included, found that after patients' data were reviewed virtually by a retinal specialist, 54 (52%) patients initially referred did not require specialist review. However, as this was a piloted system it does not represent the accuracy of referrals being made based on OCT imaging within the currently used referral pathways and did not meet the inclusion criteria for this review. A study by Jindal et al (12) found that the use of OCT scans along with fundus imaging improved community optometrists' diagnostic sensitivity for both optic nerve and retinal abnormalities for clinical vignettes; however, this study only assessed diagnoses and not optometrist referral suggestions. Thus, during the literature review no studies were identified which assessed the effect of the adoption of advanced ocular imaging on the accuracy of referrals in currently used referral practice meaning the effect this may have had in recent years could not be assessed.

2.4.8 Enhanced Referral Schemes

Within the UK, an oversubscription to ophthalmic hospital services has led to interventions which attempt to improve referral accuracy and ultimately reduce the number of false-positive referrals being seen in secondary care face-to-face clinics. Two of the reviewed studies also assessed the success of a scheme for cataract referrals through an established direct referral system where accredited optometrists perform a dilated fundus examination, discuss cataract surgery with the patient and use a cataract-specific proforma to achieve a higher level of referral quality. These studies reported the highest listing rates when the enhanced route was used of 83% (23) and 100% (15) compared to referrals via the GP through the standard referral pathway.

In some areas, asynchronous virtual review of optometric referrals carried out by ophthalmologists is also being used or has been trialled. This method aims to virtually triage referrals and was reported to reduce the number of patients (for suspected retinal pathology) being seen face-to-face within the HES by 52% during a pilot study in the UK (67). Such pathways can improve two-way communication between primary and secondary care and allow feedback to optometrists, which is significantly lacking within standard referral pathways (68). This feedback could help optometrists keep up to date with outcomes of patients they have previously referred and avoid a number of unnecessary re-referrals. It could also act as a learning aid, enabling them to make better management decisions if/when encountering similar cases in the future.

Another enhanced service scheme in place across different areas of the UK and Australia is glaucoma referral refinement. Referral refinement schemes have been successfully implemented in some areas and have reported to improve the accuracy of glaucoma referrals (27, 59, 69) as well as being potentially cost-saving for the NHS (70) and accepted by patients (71).

A detailed evaluation of the success of the schemes discussed is beyond the scope of this review and is addressed in detail during Chapter 3 of this thesis.

2.4.9 Clinical Implications and Conclusions

Based on the reviewed studies, although overall reasonable levels of accuracy were reported for general referrals, there was a large variation in referral accuracy across different ocular conditions. Recent studies are lacking, which means the effect of increased advanced imaging on the number and accuracy of primary care referrals requires further evaluation.

For glaucoma referrals, which were covered in the most detail in the papers reviewed, the rates of false-positive and first-visit discharge were sub-optimal. This is important as glaucoma appointments are responsible for approximately a fifth of all HES workload in the UK and make up a high proportion of referrals made from optometric practice. Further development and increasing the uptake of refinement schemes for glaucoma referrals throughout the UK may help to reduce the number of unnecessary appointments seen within the HES. Referrals for cataract surgery make up the highest number of referrals from primary care optometric practice. Communication between optometrists and patients regarding visual symptoms and willingness for cataract surgery could improve listing rates and reduce waiting times.

Approaches have already been made to reduce the high number of false-positive referrals, but with eyecare systems across regions varying greatly, it is difficult to determine the most-efficient way to address the problem. The College of Optometrists clinical management guidelines provide clear advice for the referral of suspected ocular conditions; however, for conditions such as glaucoma, specific guidelines in relation to a risk assessment based on specific clinical findings and patient history are lacking in England and may be a useful resource to improve the accuracy of referrals made from primary care.

Another approach is to focus on the widespread development of virtual referral pathways in order to reduce unnecessary face-to-face clinic time, reduce patient waiting times and anxiety, improve care and increase cost effectiveness. Additionally, virtual pathways would hopefully promote two-way communication between primary and secondary care to encourage feedback on referrals, which would particularly benefit those optometrists with less experience to learn and improve the accuracy of their referrals.

Overall, based on this review, optometrists' referral accuracy can be considered sub-optimal, however it may be unreasonable to expect an optometrist working in primary care, with limited time and varied resources, to achieve high diagnostic accuracy. One could argue that optometrists are working within their scope of practice and that choosing the cautious option of referral is in patients' best interests, especially when they feel uncertain of a diagnosis. Hospital eye clinics are overrun, and approaches should be made to improve referral accuracy as far as possible to reduce unnecessary face-to-face appointments.

Chapter 3: The Effectiveness of Interventions for Optometrist Referrals into Secondary Care Ophthalmology: A Review

Parts of this Chapter have been published in the following paper:

Carmichael J, Abdi S, Balaskas K, Costanza E, Blandford A. The effectiveness of interventions for optometric referrals into the hospital eye service: A review. Ophthalmic and Physiological Optics. 2023 Nov;43(6):1510-23.

3.1 Introduction

As outlined during Chapter 2, in the UK, most referrals to the HES originate from primary care optometric examinations, with a large number of these being considered 'false-positives' (12, 17), that contribute to demand on an already over-burdened HES. Recognising the need for intervention, several approaches have been trialled to tackle the high numbers of referrals from primary care. For example, in glaucoma care, referral filtering schemes have been implemented to 'triage' low-risk patients by optometrists with higher training and certification (72) through repeating, enhancing or refining the findings from the community eye exam before deciding whether onward referral is appropriate. More recently, with the advancement of ocular imaging, there has also been a focus on the implementation of teleophthalmology services for asynchronous referral review and triage which has been shown to reduce the number of unnecessary referrals for retinal disease from entering secondary care ophthalmology (67, 73). Furthermore, the significant surge in the development of artificial intelligence (AI) for medical imaging (74, 75) has highlighted a potential for its use for a range of applications including eye care. Of course, these AI systems require rigorous evaluation before implementation.

This review explored the literature for interventions that have been implemented or piloted to reduce the number of false-positive referrals entering face-to-face ophthalmology clinics. The findings were used to determine aspects of each approach that have been successful or unsuccessful and to get an overview of which approaches are being focussed on in different areas within the UK and globally.

The overall objective of this narrative review was to explore the interventions that have been implemented to try and reduce the number of inappropriate referrals being seen in ophthalmology. The review aimed to answer the following specific questions:

1. What approaches have been made to try and reduce the number of false positive referrals seen in face-to-face ophthalmology clinics?

2. How successful have these approaches been in reducing the number of false positive referrals seen in the hospital eye service?
3. Are these approaches sustainable? i.e., are they cost-effective, safe and accepted by stakeholders?

3.2 Methods

3.2.1 Registration

The international prospective register of systematic reviews (PROSPERO) was used to register the review protocol (registration number: CRD42022328773) to prevent review duplication and increase the transparency of the review process.

3.2.2 Eligibility Criteria

To complete a robust systematic search and selection of studies, a checklist of inclusion and exclusion criteria was created. This was to ensure consistency when screening articles and to act as a reference point when making decisions about whether to include/exclude articles. The decision was made to exclude studies that assessed diabetic screening referrals because, although many optometrists work as diabetic screening graders and make referral decisions, this pathway does not represent the typical primary care referral pathway. Table 13 summarises the inclusion and exclusion criteria.

Primary studies were included that used a quantitative, qualitative or mixed-methods design and were written in English. Studies were not excluded based on an assessment of methodological limitations, as described below, but the information about methodological limitations was used to assess confidence in the findings. Abstracts without a corresponding full paper were excluded, as they were unlikely to provide sufficiently rich data.

3.2.3 Search Strategy

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was used to guide the protocol development. PUBMED, MEDLINE and CINAHL were searched for potential studies for inclusion. Initially, a search was also performed using Google Scholar, but this returned many irrelevant results, with relevant papers being duplicated from the other databases. Search strategies were developed for the databases. Studies published during or after December 2001 were included to ensure an assessment that is representative of recent practice. Table 14 presents the final facets and keywords used when searching databases. In addition to database searching reference lists of all included studies were reviewed and other key references which allowed a method of 'reference chaining'.

Criteria	Inclusion	Exclusion
Time Period	Dec 2001-Dec 2022	Prior to Dec 2001
Language of original study	English	Any other language
Study Design	Qualitative, quantitative and mixed method designs including (but not limited to): controlled, uncontrolled studies, observations, interviews, surveys, retrospective analysis, clinical vignettes.	Viewpoints, editorials, conference/meeting abstracts, expert opinions and grey literature. Systematic or similar reviews (e.g., narrative, scoping and realist reviews).
Setting	Any setting involving primary eye care	Secondary care internal referrals, GP referrals, self-referrals, referrals from a diabetic retinopathy screening programme
Participants	Studies focussing on primary care optometrists making referrals to secondary care.	Studies focussing on referrals from GPs, diabetic retinopathy screening programmes, other allied health professionals or patients who self-refer (e.g., patients attending accident and emergency (A and E) without the recommendation from an optometrist).
Condition focus	Any eye condition or conditions (can include anterior and posterior eye conditions).	Referrals by optometrists to non-ophthalmology services due to systemic conditions showing signs in the eye (e.g., referral to GP for blood pressure check due to mild hypertensive retinopathy).
Topic focus	Interventions that have been implemented, trialled, or piloted. Studies do not just need to focus on the clinical outcome of these interventions. They may focus on other measures of effectiveness. Interventions can take place anywhere along the referral pathway.	Programmes or schemes that have been implemented to improve referral systems but not to reduce or triage referrals.

Table 13: Summary of the inclusion/exclusion criteria

Number Assigned to Facet	Facet	Keywords	Boolean
1	Optometrist	1. Optometrist(s) OR 2. Optometry OR 3. Primary eye care OR 4. Primary eye clinic(s) OR 5. Optician(s)	1 AND 2
2	Referral Practice	1. Referral(s)	

Table 14: Facet terms and their keywords used for database searching.

3.2.4 Selection Process

All articles identified from database searches were organised in EndNote and duplicates were removed. The primary researcher (JC) conducted screening of the title and abstracts of all search results. A second researcher (SA) also screened all titles and abstracts. Initially, a sample of 20% was screened by both researchers to assess agreement. All articles where the researchers disagreed were reviewed together and differences in interpretation of the inclusion/exclusion criteria were discussed at this stage. The remaining studies (80%) were screened by both researchers independently with a good level of agreement (kappa=0.837 95% CI 0.771 - 0.903). Studies where the two reviewers disagreed were discussed and a decision was reached to include/exclude each one. After the screening phase, 111 studies met the criteria for full-text assessment.

The full texts of all 111 studies were assessed by the primary researcher. The secondary researcher screened the full text for a sample of 20% (22 studies) and agreement was checked. Due to a small sample size, kappa agreement could not be calculated. There was 90.9% (20/22) agreement between the two reviewers. For two studies, the reviewers initially disagreed, but after discussion based on the inclusion/exclusion criteria they agreed that both studies should be excluded.

3.2.5 Data Collection and Items

Data collection was carried out by one reviewer (JC) who worked independently. Prior to collection, a form was designed to extract all relevant data from each included study. This form was part of a study protocol which was written by JC and reviewed by SA and AB prior to data extraction. Table 15 summarises the information extracted from each article.

Information Extracted	
1	Author(s)
2	Year
3	Title
4	Country
5	Study aim(s)
6	Study design
7	Sample period
8	Sample size
9	Eye condition(s)
10	Type of intervention
11	Main Results
12	Limitations
13	Other important findings

Table 15: Information Extracted from all studies included in the review.

3.2.6 Quality Assessment

In this review, papers which are the most relevant were focused on, rather than papers which met a specific standard of methodological quality. This approach has previously been described as prioritising 'signal' over 'noise' (19). Rather than excluding studies based on quality, they were included but critiqued during review to ensure transparency (20). When critiquing study quality, there was a focus on sample size for referrals, number of optometrists from which the referrals originated, number of practices from which the referrals originated, study design with respect to prospective or retrospective analysis, and the appropriateness of any statistical methods that were used.

3.2.7 Synthesis of Results

A narrative synthesis approach (76) was taken when reporting the results. This method was chosen to provide a detailed assessment of studies into different clinical interventions, whilst keeping an exploratory approach. The aim was to keep the research question broad with respect to study focus and definitions used across the studies; the review is therefore more aggregative than interpretive. The results were summarised with respect to types of interventions and the outcomes assessed. The Economic and Social Research Council guidance on the conduct of narrative syntheses (21) were referred to when carrying out this review to increase transparency and trustworthiness. The framework consists of four elements:

1) Developing theory of how the intervention works, why and for whom
2) Developing a preliminary synthesis of findings of included studies
3) Exploring relationships within and between studies
4) Assessing the robustness of the synthesis

3.3 Results

3.3.1 Study Selection

Fifty-five studies were selected for analysis. The results from the search and selection process are shown in Figure 1.

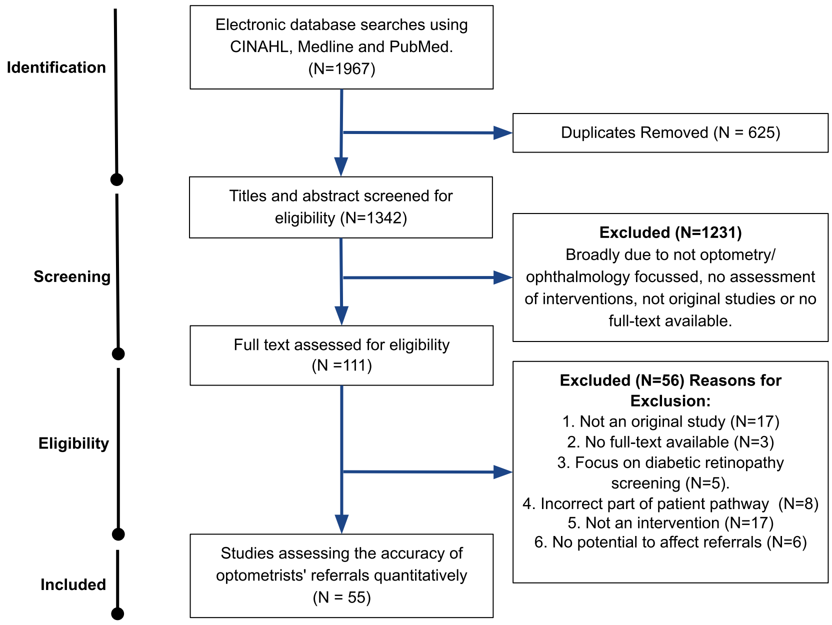

Figure 3: PRISMA flow chart detailing the selection process for the studies reviewed.

3.3.2 Study Characteristics

Details of the 55 reviewed study designs can be found in Figure 4 and in the Appendices. When reviewing the literature, it was clear that there were several different interventions that had been implemented or piloted to improve the accuracy of referrals. These interventions could be categorised into four groups:

1. Training and guidelines
2. Referral filtering schemes
3. Asynchronous teleophthalmology
4. Synchronous teleophthalmology

Some studies used multiple approaches and were therefore included in more than one type of intervention category. In this section, the outcomes reported within these four groups are discussed and their success indicators are considered for both reducing false positive referrals, and to determine their safety and sustainability.

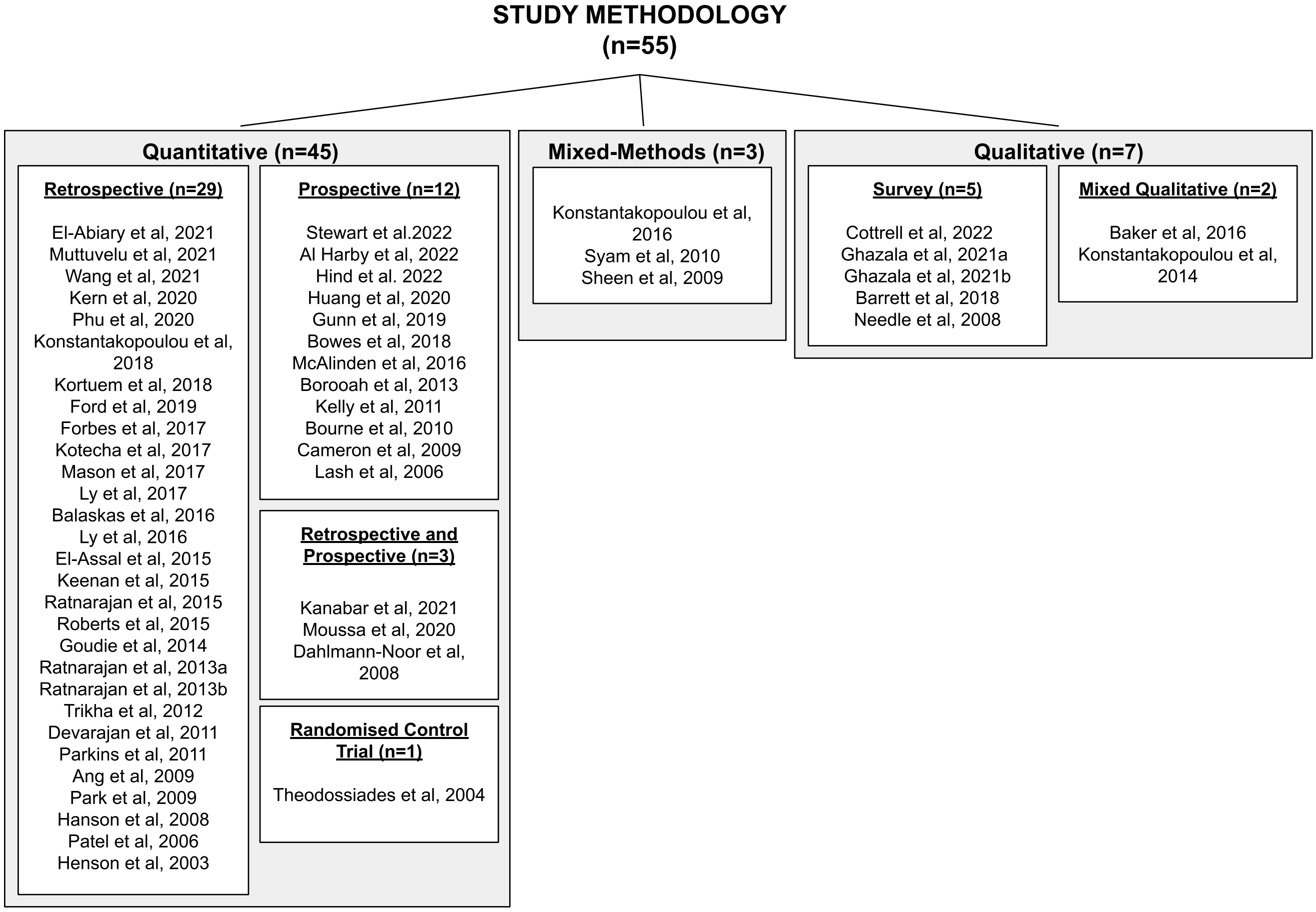

Figure *4*: An overview of the methodology used in each of the 55 studies reviewed.

3.3.3 Training and Guidelines

One approach for improving the accuracy of referrals was to focus on improving the skills and knowledge of community optometrists as the main source of ophthalmic referrals from primary care and/or introducing clear clinical guidelines that can be followed when making referral decisions. A summary of the studies focusing on this approach can be found in Appendix 1.

The most recent of these studies (34) assessed the impact of implementing clear referral guidelines set out by the SIGN (57). These provide guidance on the primary care assessment of patients with suspected glaucoma and clear referral criteria for optometrists practising in Scotland. Following the publication of these new guidelines, that study reported a significant decrease in HES glaucoma clinic first discharge rates from 29.2% to 19.4% (p=0.004) due to a lower proportion of patients being referred unnecessarily to clinics.

Two studies carried out in England assessed the impact of formal training sessions on the accuracy of glaucoma referrals. One study by Theodossiades et al. (29) focussed on training in optic nerve evaluation as well as providing referral criteria. They reported that the proportion of referrals from the intervention group resulting in a positive outcome (positive predictive value (PPV) = 0.49) was very similar to that of the control group (PPV = 0.46). A follow up from this study (77), which assessed the impact of ongoing training every 4 months, found that the training had resulted in a 58% increase in the number of referrals compared to the original study; however the PPV remained very similar (PPV = 0.51). Thus, for these two studies, participants appear to have been detecting more true-positive cases, but they had not improved their skills for confidently ruling out glaucoma in patients without the disease. Glaucoma suspects are encountered infrequently in primary care practice, meaning it is difficult for optometrists to confidently rule out the disease, particularly in its early stages. Its characteristically progressive nature means that even within the HES, more than one follow up may be required before patients are determined to not have the disease (24).

For training and guidelines to be deemed successful interventions, they must also be sustainable. No literature addressing the cost-effectiveness of the training described was found. There were, however, studies addressing optometrists' uptake and opinions towards further training. In a survey study published in 2008 (78), assessing optometrists' opinions on the Department of Health's announcement that with suitable qualification, optometrists will be able to train as independent prescribers (IP), only 9% reported no intention of undergoing further training for prescribing. However, optometrists expressed concerns such as a lack of time for training being a substantial barrier for 64% of respondents. Although that study is now dated, the findings may partially explain why a more recent study (79) found that less than a quarter (23.4%) of optometrists hold an independent prescribing (IP) qualification in Scotland. Barriers to extra training must be considered when implementing training programmes for primary care optometrists to maximise uptake, especially since health boards in Wales with IP optometrist commissioned services had fewer total and urgent referrals to ophthalmology compared to health boards with no IP optometrists during 2020 (80). However, as the study reporting these findings took place in 2020, during the COVID pandemic, results may not truly represent the demographic of patients usually presenting to primary care services.

3.3.4 Referral Filtering Schemes

Another approach that has been adopted in the UK, as well as in other countries, to improve referral accuracy, is to introduce referral filtering schemes. These schemes also utilise the interventions of training and guidelines but specifically for funded pathways where optometrists perform additional testing and assessment and act as a triage for low-risk patients. For glaucoma, there are three types of filtering schemes that have been implemented: repeat measures where intraocular pressure (IOP) and/or visual fields are repeated prior to making a referral decision, enhanced case finding where optometrists undertake a higher level of assessment compared to repeating measures and finally, glaucoma referral refinement which offers a level of testing by certified optometrists which is sufficient for glaucoma diagnosis (70). Previous reviews have assessed the effectiveness of these individual schemes (81). One aim of this review as to update the literature in this area as well as compare these schemes to other types of interventions. This review identified many studies meeting the inclusion criteria (n= 32) which focussed on this approach (Appendix 1). Due to this large number, a summary of the studies for this type of intervention is displayed, grouped by the factor(s) focussed on when assessing the scheme (Table 16).

Focus	Author(s)	Year	Location
Cost Assessment	Forbes et al.	2019	UK
	Mason et al.	2017	UK
Acceptability	Barrett and Loughman	2018	Ireland
	Baker et al.	2016	UK
	Konstantakopoulou et al.	2014	UK
Clinical Impact	Kanabar et al.	2021	UK
	Huang et al.	2020	Australia
	Phu et al.	2020	Australia
	Gunn et al.	2019	UK
	Konstantakopoulou et al.	2018	UK
	Ly et al.	2017	Australia
	Ly et al.	2016	Australia
	McAlinden et al.	2016	UK
	El-Assal et al.	2015	UK
	Roberts et al.	2015	UK
	Keenan et al.	2015	UK
	Ratnarajan et al.	2015	UK
	Ratnarajan et al.	2013a	UK
	Bourne et al.	2010	UK
	Ang et al.	2009	UK
Mixed Focus	Wang et al.	2021	Australia
	Ford et l.	2019	Australia
	Konstantakopoulou et al.	2016	UK
	Ratnarajan et al.	2013b	UK
	Devarajan et al.	2011	UK
	Parkins and Edgar	2011	UK
	Syam et al.	2010	UK
	Sheen et al.	2009	UK
	Henson et al.	2003	UK

Table 16: Summary of studies focusing on referral filtering schemes, grouped based on outcomes assessed.

Clinical Impact

The evidence suggests that referral filtering schemes are clinically effective for triaging and managing patients that do not require ophthalmology review. Studies have reported that between 35-71% of patients were discharged after first assessment within the schemes for glaucoma referral filtering and therefore not referred on (60, 82-85). In Scotland, false positive glaucoma referrals significantly reduced (36.6% to 21.7%, p=0.006) following a new GOS contract in 2006 which funds community optometrists to perform supplementary examinations in glaucoma case finding (33) with a later study (86) supporting these findings.

Four UK studies reported the outcomes of patients seen as part of a scheme set up for patients with recently occurring minor eye problems (MECS). These studies reported that between 66-75.3% of patients were managed by their optometrist without referral, either through first visit discharge or follow up by their optometrist (87-90) and only 15.9-18.9% were referred to ophthalmology(88-90). In 2020 the COVID-19 Urgent Eyecare Service (CUES) system, whereby initial screening took place via a telephone appointment by an optometrist, was adopted to allow HES clinicians to focus on more urgent eye care cases as recommended CUES nationally in April 2020. In Manchester this system resulted in only 13.0 -14.3% of cases being provisionally referred to secondary care (91). Four studies assessed the outcomes from patients seen in an Australian centre for eye health set up as an intra-professional optometry-led collaborative eye care clinic to triage patients referred for non-urgent conditions. These studies reported recommendation for referral in just 12-16.3% of patients depending on eye condition (92-94) and that 10.6 weeks of outpatient appointments were saved by assessing patients off-site at C-EYE-C (95).

Referral filtering schemes have also been developed for cataract referrals. Direct pathways in the UK have been introduced to ensure that the 'Action on Cataracts' guidelines are followed and that patients referred for cataract surgery are only seen within the HES when they have reduced measured vision, are symptomatic and express a willingness for surgery. Two early studies (23, 96) and one more recent study (97) reported that surgery listing rates were significantly higher (83-87%) when compared to conventional referral pathways (63-78%).

It is clear from these findings that these schemes can successfully result in a reduced number of patients being seen in the HES unnecessarily. One important clinical factor to consider, however, is the possible resultant false negative cases. Of the studies reviewed, five assessed the false negative rate of patients (59-61, 84, 95), all of which assessed referral filtering schemes for glaucoma. These studies reported a false negative rate of between 2-15% when either reviewed virtually or face to face. To improve clinical safety, some studies added an element of virtual review of all discharged patients as a failsafe. However, this required additional costs and resources (61, 84).

Cost Assessment

In two Australian studies, a decrease in average cost per patient (95) and no apparent change in cost (94) were reported when using a newer referral refinement scheme compared to the standard pathway.

For the studies carried out in the UK, two studies reported cost saving of the MECS (90, 98) and two for a glaucoma filtering scheme (61, 72). One study by Parkins et al. (85) compared two glaucoma schemes and reported a higher saving (62%) of a repeated measures scheme compared to enhanced referral refinement (3.5%). The last two studies reported results which differed depending on the assumption that was used for comparison (82). For example, the more recent study (70) reported that whilst assuming there would be 2.3 outpatient visits avoided per person, the saving would be approximately £2.76 per patient passing through the scheme. However, when this assumption is changed to avoiding 1 appointment, there was an increase in costs of approximately £42.28 per patient. These findings highlight the difficulty of assessing cost effectiveness, as comparisons are usually based on assumptions and/or predictions.

Acceptability

The reviewed studies suggest that there is an overall positive opinion from optometrists in relation to referral filtering schemes which is essential as optometrists are required to play an active and engaged role. One recent study reported responses about the MECS scheme (99) and focused on reasons for optometrist participation, with the most common reason being for career development through experience of assessing challenging cases. Approximately

85% identified that training had a beneficial effect on their practice. Feedback from GPs and Ophthalmologists was also supportive of the referral filtering schemes (71) (99). Studies reporting patient experiences with a referral filtering scheme were again overall positive (90). One study by Konstantakopoulou et al. (87) reported that all patients (n=109) who completed a survey were satisfied, with 95% of the patients reported confidence and trust in their optometrist.

3.3.5 Asynchronous Teleophthalmology

Asynchronous review of clinical information has been used as a method of discharging patients. This method utilises a 'store-and-forward' approach of information uploading with review later. The benefit of these systems is that patients can receive a clinical opinion from a specialist clinician (ophthalmologist or optometrist) without having to be seen face-to-face. Four studies assessing systems using this approach used datasets from at least 10 years ago (17, 100-102) whereby general ophthalmology or retinal referrals were sent by primary care optometrists with photographs attached. All four studies reported positive impacts on patient outcomes with 34-48% reviewed virtually identified as not requiring referral for face-to-face review. This value increased to 80.5% in a more recent Danish study (73), perhaps due to improved quality of ocular imaging.

To further improve the ability of clinicians to triage patients virtually, more information may be uploaded for review including advanced ocular imaging such as OCT which is now more widely available in primary care. Two studies included the uploading of OCT imaging along with fundus photographs (67, 103). The more recent study from the UK (67) assessed referrals, specifically for retinal conditions, and found 52% of the patients classified into the referral pathway did not require specialist referral.

Technician-delivered, hospital-based clinics including ocular imaging have become another useful way to review new patient referrals (104, 105). The successful upscaling of the virtual clinical capacity for glaucoma patients at Moorfields Eye Hospital (MEH) now means that all new routinely referred patients (around 5000 per annum) can be seen virtually (106). In a pilot clinic design, a recent study reported substantial agreement between the diagnosis reached by clinicians reviewing patients with suspected lid lesions face to face compared to when photos of the lesion were reviewed by consultants (107).

It is clear from the results discussed that asynchronous review of referrals can successfully reduce the number of patients needing to be seen face-to-face in ophthalmology. However, it again must be considered whether this method of triage is safe and sustainable. For glaucoma diagnosis, NICE guidelines recommend that patients undergo testing with traditional in-person review, including standard automated perimetry, Goldmann applanation tonometry, anterior chamber angle assessment with gonioscopy, and dilated optic nerve and fundus examination with slit lamp biomicroscopy (108), with the latter three tests not possible in a technician-led virtual glaucoma clinic. Only one study by Kotecha et al. (109) assessed the false negative rate of the asynchronous referral scheme for glaucoma and found that 20% seen for a face-to-face appointment after being discharged virtually were determined to require ophthalmology review (4% of which required medical intervention and were considered as 'significant' false negatives)(109). Another study reported that 40% of patients were discharged without intervention from a clinic assessing eyelid lesions, whereas discharge was recommended in 51.6% for the same set of patients when reviewed virtually. Of note, the virtual reviews were performed by a separate ophthalmology consultant in the latter study (107). In relation to the sustainability of these systems, no information about cost was reported and it was unclear from the literature how acceptable these systems were to the stakeholders using them. Just one study by Cameron et al. (17) reported patients' opinions on being reviewed virtually, with only 3/114 patients stating that they preferred face-to-face review over virtual assessment.

3.3.6 Synchronous Teleophthalmology

Virtual patient assessment via teleophthalmology is also possible synchronously, meaning that patients do not have to be seen face-to-face to be examined in real-time. Synchronous teleophthalmology is not just useful to avoid in-person contact with patients (particularly for safety reasons during the COVID-19 pandemic) but can also be used to connect primary care optometrists to secondary care physicians during an examination.

Five studies focussed on the assessment of synchronous teleophthalmology services which were implemented in response to the COVID-19 pandemic. One study by Ghazala et al. (110) used a live platform for a range of different ophthalmic conditions and reported that pre-lockdown, using this system, 50/78 (64.1%) of referrals to secondary care had been avoided. During lockdown, this increased to 65/76 (85.5%). Another approach was using telephone triage (111). One study by Kanabar et al.(91) assessed a telephone triage service manned by HES allied healthcare professionals and ophthalmologists. Using this system, less than a quarter (24.5%) of patients required face-to-face follow up. In Greater Manchester, 38% of patients did not require a face-to-face appointment when using remote triaging as part of the CUES scheme.

Although data was limited for stakeholder opinions, when considering synchronous video assessment the mean Likert score for satisfaction with a teleophthalmology consultation was 5/5 from optometrists, ophthalmologists and patients (112). Another study also reported that 98.5% of patients felt comfortable with the quality of a telemedicine examination, with 97.1% reporting they would participate in another one in the future (113). However, no studies reported the cost-effectiveness of these systems or the logistics of having clinicians on call, in real-time, to assess patients. Additionally, four studies were carried out during COVID-19 lockdowns meaning fewer patients would have been visiting optometrists for routine eye exams during this period. Thus, in summary, although these systems were successful for reducing the patients requiring face-to-face appointments during the COVID-19 pandemic, it is unclear whether they have all remained in place long-term.

3.3.7 Comparing Outcomes Across Interventions

Based on the studies reviewed, the evidence was summarised and presented in relation to three main outcomes used as measures of effectiveness: clinical impact, cost and acceptability. Figure 5 summarises these outcomes in relation to each intervention.

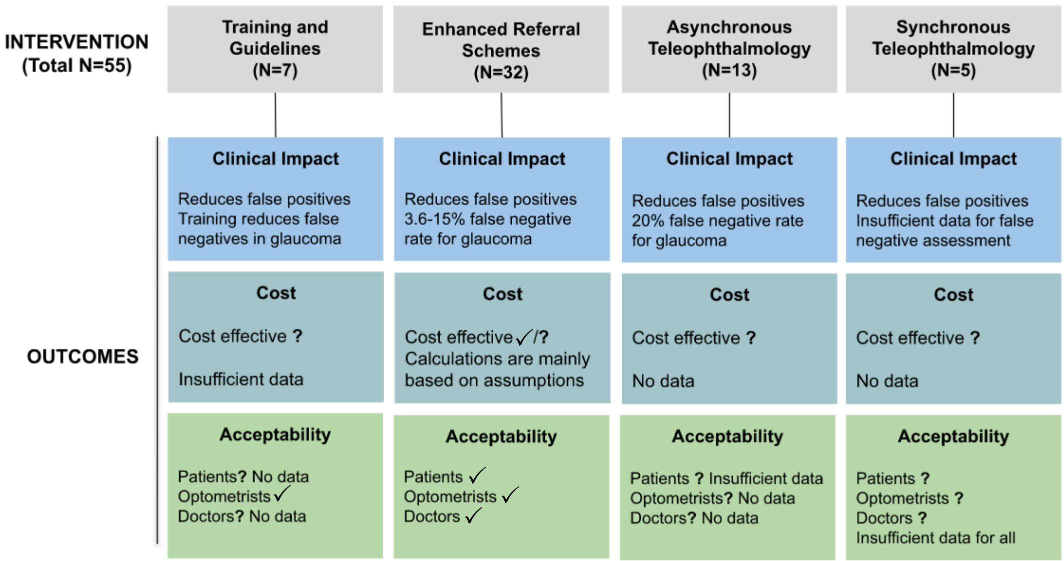

Figure 5: A summary of evidence in support of three outcome measures in relation to four types of intervention. Where the evidence supports the clinical outcome, a '✓' is displayed. Where the outcomes are not fully supported or evidence is lacking, a '?' is displayed. For outcomes which are not fully supported, the reason why this was decided is stated.

3.4 Discussion

In this section, the impact of the different interventions on the three main stakeholder groups involved is considered:

1. Patients
2. Ophthalmology Services
3. Community optometrists.

3.4.1 Impact on Patients

The effect of new interventions on patients' safety and experiences must firstly be considered. Although there was sufficient evidence to support a positive patient experience with relation to referral filtering schemes, there was insufficient evidence in relation to teleophthalmology interventions. Only one study by Cameron et al. (17) into asynchronous interventions reported patient satisfaction outcomes using a binary measure and detailed opinions into which aspects of the service patients liked/disliked were lacking. Previous studies have investigated patient satisfaction with ophthalmology virtual clinics in more depth, mainly for follow up patients. Although findings have been generally positive, such as surveys reporting a similar mean satisfaction score compared to a standard clinic, there may be concerns around the lack of contact with a clinician with some patients feeling that they would like a dialogue with a healthcare professional during each appointment (114).

One potential positive impact of all the interventions explored is the reduced waiting time between patients being referred and their review. One study by Kelly et al. (103) reported that in 96% of referrals, an ophthalmology specialist had virtually reviewed the referral and provided a working diagnosis/plan within the next calendar day. Reducing the number of false positive referrals seen face-to-face in ophthalmology would also reduce waiting times for patients with ocular disease requiring hospital assessment and treatment. Patient care and treatment can be time critical. For example, it has been reported that for patients with wet AMD, a delay in treatment of over 4 weeks can cause a loss of three lines in visual acuity. However, where referral is deemed necessary for patients, it could be argued that schemes such as enhanced referral where an extra step is added to the pathway may case delay to accessing required treatment. Only lower-risk patients are therefore deemed suitable for these pathways.

The last significant patient factor to consider is the potential for false negative cases. These represent patients with referable ocular conditions requiring ophthalmology attention and/or treatment who are erroneously not referred.. In the reviewed studies assessing referral filtering schemes, the false negative rate was up to 15% and for asynchronous patient review it was 20%, which represents a relatively high percentage of discharged patients who were considered as requiring ophthalmology review in two studies. It should be noted that a comment published in Eye in 2022 (which did not meet the inclusion criteria for review) reported a CUES scheme false-negative rate of just 0.23% for moderate-to-high risk of sight loss cases which the authors described as ‘reassuringly low’ (115). Combining more than one approach, such as referral filtering schemes with virtual review of discharged patients may increase clinical safety (84), but this would add another element of cost and resources where with adequate training, optometrists can perform safely, as demonstrated by the Manchester glaucoma enhanced referral scheme (59).

3.4.2 Impact on Secondary Care Ophthalmology

Despite there being a range of values for appointments avoided by different interventions, and some interventions only being appropriate for low-risk referrals, the evidence suggests that all four classes of interventions can have a positive impact.

When assessing the effectiveness of the different interventions how specialists' allocated work time may be impacted must also be considered. For example, if clinicians are involved in a new pathway which includes synchronous or asynchronous review of patients using teleophthalmology, this must be an efficient use of their working hours. For asynchronous review of new referrals, there is a strong argument that this is an efficient use of time as patients can be triaged virtually in far less time than they would be if they were seen face-to-face in clinic. One study by Kern et al. (67) reported that when using a cloud-based referral system for suspected retinal disease the mean review time for referral refinement was just 3.0 min in total. This review time is significantly shorter than a patient encounter in a face-to-face clinic and means that more patients could be reviewed in the same period if seen virtually. In comparison, synchronous teleophthalmology requires specialists to virtually assess patients in real-time, which is less time efficient.

3.4.3 Impact on Community Optometrists

The positive and negative effects that discussed interventions may have on optometrists and/or optometry practices must also be considered. One positive impact of implementing some of these schemes is the potential for improved interaction between primary and secondary care. When using a typical referral pathway, after a patient is seen, a clinic letter is written by the healthcare professional which summarises the appointment findings but is usually addressed to the GP only. Early studies found that referral reply rate to optometrists, either through direct reply or by copying in, varied from 13% to 16% (116, 117) due to the GP not always including the optometrists' contact details on the GOS referral, GPs don't see their role as one that passes on information to the referring optometrist, and that optometrists are transient care providers (68). Feedback as part of new pathways such as direct referrals using virtual pathways could not only keep optometrists up to date with outcomes of patients for if/when they see them again in practice but would also act as a learning aid for when they encounter similar cases in the future, enabling them to make better management decisions.

New referral pathways/schemes must also be a beneficial and cost-effective use of optometrists' time in practice. For the implementation of new direct pathways such as asynchronous, cloud-based referral platforms, the systems must be intuitive for optometrists to easily refer patients in a time-efficient manner. Similarly, for optometry practices to be willing to take part in referral filtering schemes, the clinical time allocated to seeing these patients must be cost-effective for practices through sufficient remuneration from local or national funding. In England, the limitation of the GOS contract is one of the main issues with community eyecare (118). Unlike the GOS contract in Scotland, there is no additional funding for supplementary tests, and additional test time, which are essential for referral filtering. Local funding of such schemes presents an issue with their sustainability and creates differences in local guidelines between regions. Even with allocated funding, some practices may choose not to sign up to deliver a service such as MECS or to offer limited appointments, as the cost of the appointment may not be fully subsidised. Additionally, the likelihood of a sale taking place is reduced when the purpose of the appointment is focussed on an ocular health concern which poses a problem for optometric primary care which uses a cross-subsidisation business model (i.e. using the sale of optical products to subsidise money lost from eye examinations).

3.4.4 Missing Information

There were two main features which were lacking in the body of reviewed literature. Firstly, this review was intended to be a mixed-methods review, whereby a broad range of literature of both quantitative and qualitative methods were included. However, although some included studies used qualitative methods, the vast majority were studies using quantitative measures. This meant an inability to gain qualitative insights into some of the interventions and a reliance on speculation to determine explanations for the quantitative findings.

Secondly, the potential use of AI to improve the accuracy of referrals was not covered. A great deal of research is currently focusing on AI for aiding the diagnosis and management of ophthalmic conditions (119-122). AI systems specifically for diabetic retinopathy screening in primary care are already being implemented and piloted in real-world settings. A small number of non-UK studies have reported on safe systems (123-125) with a positive impact of increasing attendance when used as a point of care device (124), as well as potentially reducing the burden on current screening services (123). Although optometrists have expressed positive attitudes towards the future use of AI in primary care as a diagnostic tool for retinal disease, there were no studies found that implemented or piloted AI specifically for the diagnosis/management of patients referred from primary care optometry. The HERMES study protocols (126, 127) describe a pilot which is currently taking place using a cluster randomised trial to evaluate a teleophthalmology referral pathway for retinal disease, which included the assessment of the accuracy of an AI diagnostic support system for automated diagnosis and referral recommendation. However, results from this clinical trial are yet to be published.

3.4.5 Limitations

There were two main limitations to the review, which were based on the search strategy and inclusion/exclusion criteria. Firstly, studies were excluded that focussed on diabetic retinopathy assessment and screening. This decision was made as pathways for diabetic retinopathy referrals, certainly in the UK, do not follow the typical referral route from primary to secondary care. Patients with diabetes are usually seen within a screening service which runs parallel to standard pathways from primary care optometrists, so assessing interventions to this pathway would not fit in with this study focus. However, it is acknowledged that over recent years, advances have been made in the use of AI technology for diabetic retinopathy screening and grading, and that four studies (122-125) were excluded which specifically focussed on real-world AI implementation, which was lacking in the reviewed literature. Furthermore, studies not published in English were excluded, which could have limited diversity with relation to their country of origin.

Secondly, a broad search and inclusion criteria was used in relation to study focus and study design and completed no formal quality assessment of the included studies was completed. Although this highlights a strength of the study, in that it allowed a broad overview of interventions which included both a quantitative and qualitative perspective, whilst considering a range of success factors, it meant that directly comparing studies was difficult and that a statistical approach was not appropriate.

3.4.6 Clinical Importance and Conclusions

Overall, the review highlights that the implementation of a successful intervention for reducing false-positive referrals is more complex than a 'one-size-fits-all' approach. Firstly, certain interventions are more established for specific eye conditions. Referral filtering schemes for example appear to run well for conditions such as glaucoma and cataract but there was no evidence for similar schemes for routine referrals of suspected retinal conditions. This lack of evidence is perhaps due to referrals for suspected retinal disease being less frequent and more diverse, making it difficult to implement a structured refinement scheme. In contrast, using asynchronous review of clinical information by ophthalmologists is useful for the quick triage of suspect retinal conditions, but would not be appropriate for cataract referrals a conversation around symptoms and willingness to undergo surgery must take place.

The effectiveness of each type of intervention also varies based on what outcome is being considered as a measure of success, and which stakeholder is the focus. From the studies in this review, there was sufficient (33) evidence to support the positive clinical impact of all interventions discussed, in reducing the false positive referrals being seen face-to-face within ophthalmology, but evidence around cost-effectiveness of all interventions is either insufficient or conflicting. Furthermore, more studies are required to explore stakeholder opinions around these interventions, and there is less of a drive to publish negative stakeholder views when schemes produce clear benefits for easing the strain on secondary care ophthalmology.

To maximise the safety of these interventions, it may be useful to combine more than one approach, such as referral filtering schemes with virtual review of discharged patients or for some community schemes such as MECS to be operated only by those with extra training in independent prescribing. Of course, this would require additional costs and resources, and there is no one-size-fits-all solution. Although the literature search found no assessment of implemented AI systems for the specific focus, the increasing availability of AI systems means that there is potential for AI to play a role in clinical decision support systems within referral pathways from primary care in the future.

Chapter 4: AI in Healthcare

4.1 Introduction

Artificial intelligence (AI) is emerging as a transformative force within healthcare, with its ability to analyse complex medical datasets (128), identify patterns, and support clinical decision-making processes (129). Its integration into CDSS represents a significant shift in how healthcare professionals may access and apply information in real-time practice.

This chapter provides a critical review of the literature on AI applications in CDSS, with a specific emphasis on ophthalmology. It begins with examples of how AI has been applied within ophthalmology across a range of conditions with particular attention given to recent innovations in AI for OCT interpretation, due to its relevance in this thesis for its application in primary eye care and its potential to influence optometric referral decisions.

Subsequent sections address the importance of human-computer interaction considerations in CDSS implementation and highlight considerations for human-computer collaboration, including ways in which AI can be designed to complement, rather than replace, the clinician. The concept of trust in AI is also explored, as trust is recognised as a critical factor influencing clinicians' acceptance and use of AI tools. Finally, the chapter examines the role of explainability in AI-CDSS, with a focus on the potential of saliency and segmentation maps to enhance interpretability and clinical utility. Taken together, this chapter highlights both the promise and the challenges of integrating AI into ophthalmic practice.

4.2 Background: AI in Ophthalmology

Perhaps some of the most exciting recent developments in ophthalmic care have been made in AI. Many in the medical industry are beginning to view AI as the most promising technology for medicine (130), and while its potential is just beginning to be uncovered, systems have already been developed for uses in a wide range of ophthalmology applications. In the following sections I will discuss some of the most notable developments in this research. The sections are structured by eye condition before introducing the literature that focuses specifically on retinal OCT interpretation; the focus of this thesis.

4.2.1 Diabetic Retinopathy Screening

AI has demonstrated significant potential for the detection, grading and prediction of diabetic retinopathy (DR)(131). Notably, Abramoff et al’s work (132), published in 2018, carried out a trial of an autonomous AI-based system for DR detection and diagnosis, where retinal images from 819 patients with diabetes at 10 different primary care sites were used to identify and grade DR. The system achieved a sensitivity of 87.2% and specificity of 90.7% for detecting 'more than mild DR' (mtmDR). As a result of this trial, the FDA authorised the AI system for use by healthcare providers to detect mtmDR in patients over the age of 22, with no history of previously detected DR.

Since then, numerous other studies have assessed the use of AI as a screening tool for DR. A multicentre validation study in the U.S. assessed seven AI diabetic retinopathy screening algorithms and found that all algorithms showed high negative predictive values (133). Another study demonstrated significant potential for AI use for DR screening in low-income countries facing critical shortages of health facilities and where progression from no DR to vision-threatening DR is around five times in comparison to European studies (134). That study, by Bellemo et al (135), validated an AI model for the classification of DR in retinal fundus images, on 4504 images from African patients in Zambia, obtained within real-world clinical settings, and reported excellent detection rates for vision-threatening DR and diabetic macular oedema (DMO) (sensitivities 99·42% and 97·19%, respectively), which highlights the potential for introduction into screening areas with varied resources.

Overall, AI has been widely recognised, based on numerous prospective studies, such as the ones discussed, as a highly accurate tool for detecting referable and vision-threatening diabetic retinopathy, making it potentially suitable for use in primary care screening programmes. A key indicator of effectiveness includes improvements in screening attendance, with some evidence suggesting that point-of-care AI may enhance follow-up rates. For example, a randomised controlled trial at Johns Hopkins Hospital in Baltimore, USA, found that point-of-care autonomous AI diabetic eye exams significantly increased screening completion rates in young people with diabetes (100% vs. 22%)(136). Follow-up with an eye care provider after abnormal results was also higher in the AI group (64% vs. 22%). The study highlights

AI’s potential to improve early detection and access to diabetic eye care in diverse populations.

Cost-effectiveness is also a factor to be considered if implementing AI in screening. Studies from the UK and Singapore show that semi-autonomous models can offer greater cost savings than either full automation or human grading. The NHS Diabetic Eye Screening Programme found that semi-autonomous use of machine learning algorithms was more cost-effective than human grading (137). Similarly, a cost-minimisation study in Singapore showed that semi-autonomous screening was more economical than both autonomous AI and human grading (138).

In parallel with these developments, some studies have explored how such DR AI screening tools could be integrated into routine clinical practice as CDSS. These investigations consider not only diagnostic performance but also workflow integration and clinician interaction. These HCI focussed studies are discussed in Section 4.6, with attention to the design and implementation challenges.

4.2.2 Glaucoma

AI has shown significant promise for use in detecting glaucoma and assessing worsening of disease. For example, The Artificial Intelligence for Robust Glaucoma Screening challenge assessed 14 AI algorithms using 113,000 fundus images from 60,000 patients across 500 screening centres and best-performing models matched the accuracy of 20 eye care professionals and demonstrated strong generalisability across three external datasets (139). Wang et al (140) demonstrated that AI was useful and accurate in assessing glaucomatous visual field plots to identify progression. Another study developed an AI-based structure-function map to relate damage identified via OCT imaging to function loss on visual field testing (141).

An exciting application of AI in glaucoma care is its potential to detect sub-clinical signs of the disease, enabling earlier diagnosis of sight-threatening conditions before they become apparent through conventional testing, potentially preventing irreversible sight loss. Asaoka et al. developed a system which assessed visual field results, to detect pre-perimetric (before presenting with any visual field loss) glaucoma (142), with the results suggesting that early glaucomatous visual field change can be observed in patients thought to have pre-perimetric glaucoma. This highlights its potential as powerful clinical support tools that could act as an alternative for identifying pre-perimetric glaucoma when imaging devices are unavailable. However, one limitation of this study is that it lacked external validation on an independent dataset.

4.2.3 Anterior Eye

AI in ophthalmology may also be used to increase knowledge of unusual eye conditions that are not yet well understood. For example, various ML algorithms have been designed and tested for detecting keratoconus (KC), a progressive corneal condition, where underlying aetiology remains incompletely understood.

A recent paper by Shi et al (143) developed an automated classification system using a machine learning classifier to distinguish sub-clinical KC from healthy controls. Another study developed an algorithm which effectively assessed local versus global progression of KC, to identify which may need cross-linking treatment, which is used to stop disease progression, earlier than others (144). Earlier identification and treatment of disease progression could help limit the progression of keratoconus earlier in some patients to preserve vision.

A review paper (145) assessed the literature on machine learning for KC which covered a range of imaging modalities and indices, subject groups, labelling methodology and output comparison groups. In general, this review concluded that all studies included demonstrated very good differentiation of KC eyes from healthy controls. However, the difficulty in sourcing large datasets meant that earlier studies report only small sample sizes. Although there has been a trend of increasing sample sizes over time, development of machine learning algorithms for other conditions have been accelerated by the creation and availability of public datasets, which are not yet available for KC.

4.2.4 Cataract

Research has highlighted the potential for AI use in cataract detection, management and classification of severity. One study by Zhang et al (2019) (146) used AI as a six-level, accurate, grading cataract system which was based on the degree of blurred fundus image caused by the lens opacity. This method used multi-feature extraction through applying a residual network (ResNet18). One limitation however is that, although not specified, it appears this algorithm may not work for all types of cataracts. A cortical cataract would unlikely cause significant blurring to the features but may cause significant visual symptoms.

In the area of cataract management, AI algorithms have also been developed to determine the intraocular lens power needed to replace the patient's lens during cataract surgery. For example, a recent study by Gonzalez and Bautista (147) developed an algorithm which incorporates the curvature ratio of the posterior and anterior corneal surfaces, an attribute which had not previously been considered in other AI models. This algorithm produced superior predictions of refractive error post-surgery compared to other available algorithms. However, their model was based on a training set of only 208 eyes and applied only to patients with very simple prescriptions, rather than the broader population seen in practice. The addition of more data would likely improve its accuracy.

4.2.5 AMD

Arguably the most significant condition for which AI may have an impact is age-related macular degeneration (AMD). AMD is the leading cause of vision loss in the developed world, and the number of people living with AMD is expected to increase 1.5-fold over the next 10 years (148). Thus, early screening for AMD and accurate prediction of progression to the sight-threatening forms are imperative. One study by Grassmann et al (149) reported a disease classifier based on pathology from retinal photographs. Burlina et al.'s (150) deep learning model also performed classification but additionally used published probabilities to predict progression at 5-years.

A more recent study by Bhuiyan et al (151) was the first to propose a colour fundus photo-based screening model for late AMD which could also predict incidence within 1 or 2 years along with categorisation of dry and wet form. Identifying these higher risk patients could lead to them potentially being referred to a HES for closer surveillance as a preventative measure. However, the model was fine turned to AMD only, without considering the often-coexisting pathologies present. Significant modifications would thus be needed before deployment into community practice. Nevertheless, this model demonstrates the exciting potential for AI in predicting late-stage AMD and potential to lead to preventative strategies or earlier treatment to reduce sight loss.

4.2.6 AI for OCT analysis

Exciting developments in ophthalmic care have been made in AI OCT interpretation and analysis in recent years. This innovation carries the potential not only to support primary care clinicians in interpreting OCT results but also to alleviate the burden on secondary care professionals who contend with the interpretation of a substantial volume of scans daily (10). One unique challenge for the implementation of AI in OCT interpretation is the contrast in use case between primary and secondary eyecare, leading to differences in AI needs and considerations for design. In primary care, AI's potential mostly lies in aiding initial screening of common eye conditions through helping optometrists, considered non-specialists, to identify when a patient requires referral to specialist care. Systems have therefore been designed to identify and differentiate various retinal pathologies. A commercial system, released in November 2022, purportedly possesses the capability to discern 49 pathologies from OCT images, achieving a cumulated accuracy of 91% (152). However, there are no published studies about this commercial system and its performance. Liu et al. (153) published findings from a similar tool for OCT multiclass interpretation with an additional feature of patient management suggestions. This system however was designed for automated AI screening and remote assessment of patients and thus did not focus on the usability of the system by clinicians. Comparatively, in secondary care ophthalmology, where specialists with advanced experience of OCT interpretation are involved, AI may assist by tracking disease progression, predicting outcomes and planning treatment and certain AI systems have been tailored to target distinct types of retinal diseases or specific pathological characteristics. An instance of this is the segmentation of age-related atrophy and its subtypes, where the system's performance closely rivals that of manual specialist assessment (154). Other examples include a system developed specifically for accurately measuring oedema (155) and one that has performed better than five out of six experts for predicting the conversion to wet macular degeneration (156).

The Moorfields-Google-DeepMind AI system (157)6, used as an example throughout this thesis, introduced a unique analysis approach by splitting the AI analysis of the OCT scan into two distinct stages and producing three types of outputs: segmentation maps, diagnostic suggestions and management suggestions. This division accommodates the variability in disease presentation across different patients and addresses variations in technical aspects of image processing. The system reached or exceeded the performance of retinal specialists for the management of a range of sight-threatening conditions. However, besides some qualitative evaluation of the AI revealing good clinical applicability for both care management and research for this specific system (158), there remains an overall limited understanding of the practical ways in which clinicians might interact with such systems within the context of their clinical decision-making. This gap in understanding therefore provides an example use case to better understand clinicians' potential future use of an AI-CDSS.

4.3 Human-AI Collaboration in Healthcare

The studies discussed, as well as numerous others, demonstrate impressive performance of ophthalmic AI. However, most research has been predicated on the comparison between the diagnostic accuracy of AI and humans, suggesting an alternative to clinicians, rather than to support them. This competitive view is an unrealistic approach, and research should also focus on how systems can be designed to work alongside healthcare professionals through human-AI collaboration (2). One well-cited study by Dietvorst et al (159)found that giving users small amounts of control over algorithms can significantly reduce aversion to use, and some form of collaboration may also increase clinical performance when compared to humans or AI alone (2).

For example, Tschandl et al (2) carried out research into image-based AI systems for skin cancer diagnosis, through assessing the effects of varied representations of AI-based support across different levels of clinical expertise and multiple clinical workflows. They found that good quality AI-based support for clinical decision-making significantly improved diagnostic accuracy over that of either AI or physicians alone. This was demonstrated by an increase in accuracy of human raters from 63.6% to 77.0% when using multi-class probabilities as support. Furthermore, in a separate experiment assessing diagnoses in clinically relevant scenarios, the diagnostic accuracy of dermatologists and AI increased from 55.6% and 53.9% respectively, to 75.0%.

Another study took a different approach in investigating human-AI collaboration, through introducing human-centred refinement tools to produce more personalised results (160). They found that, in two evaluations with pathologists assessing prostate cancer, additional human-centred refinement tools increased diagnostic utility of images retrieved by a content-based image retrieval (CBIR) system. The tools also increased user trust in the AI and improved the end user experience. Furthermore, they observed that users adopted new strategies when using refinement tools by re-purposing them to increase their understanding of the AI algorithm and test its functioning. In some cases, this also then allowed disambiguation of clinician and AI errors from each other.

Although not in the field of ophthalmology, these studies highlight the importance of research into this collaboration to increase diagnostic accuracy, improve user experience and promote acceptance into practice. They highlight the necessity to acknowledge that a one-size-fits-all approach for implementing an algorithm into clinical care is unlikely to work.

4.3.1 Medical Image Interpretation

The broader insights discussed highlight the need to examine specific domains where AI-clinician collaboration has already been trialled. Medical image interpretation provides a particularly relevant example, as it represents one of the more well-studied applications of AI in healthcare. Certain systems have demonstrated the capability to match or surpass human experts in image interpretation within other medical imaging domains, including lung cancer screening (161) and breast cancer screening (162). The use of AI tools for these types of medical applications provides an opportunity to better derive clinical value from imaging data and reshape the way patients are managed. Schaffter et al. (163) reported that using an ensemble of AI algorithms combined with radiologist assessment in a single-reader screening environment was the most efficient approach to improve overall mammography performance. The examples of lung and breast cancer screening typically focus on a binary classification task. The example case of retinal disease diagnosis involves multi-class consideration and thus a different decision-making process. Han et al. (3) designed an AI system which rendered multi-class classification among 134 skin disorders. When used by clinicians, this was shown to significantly improve their performance. Also in skin disorder classification, a similar study (2) examined whether human–computer collaboration is influenced by the way that AI outputs are presented to humans, through assessing the effects of varied representations of AI-based support. They reported significantly improved diagnostic accuracy over that of either AI or physicians alone when AI-based multiclass probabilities were used compared to other prototyped forms of support.

4.4 Integration of AI-CDSS

Despite AI systems demonstrating significant potential for use in a range of medical applications, researchers commonly encounter hurdles in seamlessly integrating AI into clinical workflows such as technical constraints and operational procedures (164, 165). Beede et al. (166) investigated the use of a diabetic retinopathy screening tool in a real-world setting in rural Thailand. They found a clear deficiency of the AI system to grade images of lower quality due to environmental influences that could not be changed-something that was unavoidable within the specific clinical setting (e.g., unable to turn off room lights in the clinical setting to prompt pupil dilation as it was being used by more than one clinic type) and with the clinical resources available. Similarly, Bach et al. (167) underscored that certain principles derived from the bias mitigation literature may not align with the practical challenges faced by clinicians.

In a study on the integration of automation in digital pathology, Molin et al. (168) studied the reflections of pathologists following the introduction of a partially automated digital workstation. They emphasized the variable importance of findings from case to case. To address user/case specific variations, Cai et al. (160) designed and tested human-centred refinement tools after exploring individual needs of pathologists (160) and Gu et al. (169) created a human-AI collaborative diagnosis tool to share a similar examination process to that of pathologists. To address the mismatches between lab-based and real-world use, Cai et al. (160), also in pathology, explored the differences between individual needs of pathologists (160). They then used these findings to develop human-centred refinement tools to allow users to input to the image retrieval system by communicating what types of similarity are most important to them at different moments in time. This user input prompted the AI to tweak its search results accordingly to produce more personalised results and increase diagnostic utility of the system.

Gu et al. (2023), again within a pathology use case, acknowledged the complexity and uncertainty of AI's outputs (169). They stated that presenting comprehensive findings with adequate explanations can create an additional cognitive burden on pathologists and that its incompatibility with current workflows is the main hindering factor to integration. As a response they too created a human-AI collaborative diagnosis tool that was developed to share a similar examination process to that of pathologists to improve AI's integration into their routine examination.

4.5 Automation Bias in Healthcare

When implementing an AI-CDSS within healthcare settings, the impact of cognitive biases on clinicians' interpretation of AI-generated outputs must also be considered. For instance, automation bias denotes the potential tendency of users to excessively rely on automation when making clinical judgments (170). This bias has been observed across various medical domains, such as in the prescription practices of general practitioners (171) and the interpretation of mammography results (172).

Another critical bias to consider in the integration of AI systems is anchoring bias. This is characterized by decision-makers being unduly swayed toward judgments that align with an initially presented value (173) often without their awareness (174). For example, Ly et al. (2023) analysed over 108,000 emergency department attendances and found that when "congestive heart failure" (CHF) was mentioned in triage documentation, prior to a physician seeing the patient, clinicians were significantly less likely to test for pulmonary embolism (PE) in patients presenting with shortness of breath. This anchoring on the initial triage note was associated with a reduced likelihood of diagnosis in the emergency setting, despite no difference in ultimate diagnosis rates. These findings suggest that early impressions can anchor decision-making and hinder appropriate consideration of alternative diagnoses (175).

In contrast, a set of controlled experiments by Bergman et al. (2022) found limited evidence of anchoring bias in medical decision-making among trained medical students assessing hypothetical mental health scenarios. Although participants demonstrated confirmation bias in selecting follow-up information, the order in which symptoms were presented did not significantly influence final diagnoses. The authors concluded that anchoring effects may be less detectable in complex, reflective decision-making processes, particularly in experimental settings involving nuanced clinical reasoning (176).

Addressing such biases becomes pivotal when introducing AI systems into clinical settings. Bach et al. (167) assessed anchoring bias using an ophthalmology use case, whereby an AI system to detect diabetic retinopathy was already in use by clinicians. They then designed and tested potential AI features to reduce the effect of this bias. These findings collectively suggest that AI systems, particularly those that make early or confident recommendations, may inadvertently reinforce anchoring biases rather than mitigate them.

While studies such as Goh et al. (2025) show that AI assistance can improve clinical accuracy without introducing demographic bias, they also highlight clinicians' willingness to modify decisions based on AI outputs (177). Such findings reinforce the need for caution: although AI tools show promise in augmenting decision-making, they have potential for inconsistent behaviour and most critically, they carry the risk of amplifying existing cognitive biases or introducing new ones, particularly among underrepresented patient groups (178, 179). Ensuring that AI-CDSS are used to support rather than replace human judgement is therefore essential to avoid overreliance and safeguard equitable, context-aware clinical care.

4.6 Clinician Trust in AI Systems

The successful integration of artificial intelligence (AI) into healthcare depends not only on technical performance, but also on clinicians' willingness to use and trust these tools. Trust in AI-based clinical decision support systems (AI-CDSS) is a multi-dimensional construct, shaped by perceptions of reliability, safety, transparency, and usability. Crucially, clinicians must develop an appropriate level of trust, calibrated to avoid both over-reliance and under-utilisation. Excessive trust may lead to uncritical acceptance of AI recommendations, even when erroneous, while insufficient trust may result in missed opportunities to benefit from valid insights. Over recent years, there has been a growing body of research into clinician trust in AI across different healthcare contexts. These studies highlight a variety of trust-related challenges and enablers, ranging from explainability and system performance to clinician experience and perceived autonomy.

Tucci et al conducted a comprehensive review of the factors influencing clinician trust in medical AI (180). They identified key attributes associated with enhanced trust, including system explainability, transparency, and usability. Importantly, they stressed the role of education and clinician involvement in the design process to ensure the systems are perceived as collaborative tools. The review also highlighted a need for ongoing evaluation of AI trust dynamics and clinician feedback as systems evolve in clinical environments.

In a conceptual and empirical study, Choudhury and Elkefi explored the initial trust formation among clinicians when using unfamiliar AI systems (181). Their work drew attention to human biases that may interfere with the development of appropriate trust. They proposed a model in which clinicians' mental workload, perceived information relevance, and patient risk all affect the thresholds at which clinicians accept AI recommendations. The authors argue that trust in AI is not simply based on system performance, but also on clinicians' perception of its alignment with their clinical judgement, values, and context.

Stevens and Stetson developed a clinician-focused model of trust and acceptance of AI (182). This validated framework was tested in real-world hospital environments and demonstrated that clinicians' specific trust in an AI system was the strongest predictor of both their immediate acceptance and their general stance toward AI in future applications. Jones et al. (183) further unpacked the conceptual underpinnings of trust and trustworthiness using a philosophical framework. They argued that trust in AI-CDSS is often discussed in ambiguous terms, and that greater clarity is needed regarding what exactly is being trusted, be it the system, its developers, or the data upon which it was trained. Their work highlighted the role of perceived legal accountability, system accuracy, and clinician autonomy as central issues shaping trust.

A qualitative study by Burgess et al. explored trust formation through iterative design testing of an AI-CDSS for medication recommendations in type 2 diabetes care (184). The authors found that clinicians often formed an initial judgement about whether to trust an AI tool early in its use. Their findings emphasised the importance of providing system transparency and contextually meaningful explanations upfront. Clinicians expressed a need to understand how the system had generated insights, particularly when recommendations diverged from their usual clinical practice and that trust was not a binary outcome, but rather a continuous and negotiable process shaped by system familiarity, explanation quality, and alignment with the clinician's own reasoning.

4.6.1 Perspectives from Optometry

Although there is an expanding literature on AI trust in general medicine, research within optometry remains limited, particularly within the UK. This is a noteworthy gap, as the scope of optometric practice varies significantly across countries, influencing both exposure to AI technologies and perceptions of their utility.

A small cross-sectional study in Nigeria by Ebeigbe et al. found that over half of participating optometrists were familiar with AI, with most expressing optimism about its ability to support diagnosis and patient care (185). However, concerns were raised regarding diagnostic accuracy, cost, and the potential threat to job security and the doctor-patient relationship.

Scanzera et al. surveyed members of the American Academy of Optometry and found similarly positive attitudes towards AI in eye care, with 72% of respondents believing it would enhance clinical practice (186). Interestingly, the COVID-19 pandemic appeared to increase willingness to adopt AI, suggesting that clinical context and pressures can influence openness to technological innovation.

In Australia, Ho et al. (240) investigated optometrists' attitudes towards AI for diagnosing retinal disease. Respondents were generally supportive of using AI as a second opinion tool rather than at the point of care, reflecting a preference for maintaining primary clinical control. Motivators for adoption included improved access to care, while concerns included diagnostic reliability and a lack of evidence supporting AI's impact on patient outcomes.

Together, these studies suggest that optometrists are generally open to adopting AI, but that trust is conditional. It depends on clarity about the system's purpose, evidence of clinical benefit, and the assurance that AI will support, not replace, professional judgement. The scarcity of UK-based studies is a limitation, given the distinct structure of primary care optometry in the UK, and further research is needed to assess trust factors in this setting.

4.7 Explainable AI

The 'explainability' of clinical AI systems can ensure transparency about how AI arrives at its conclusions. In healthcare, where decisions significantly impact patient outcomes, understanding the reasoning behind AI-generated recommendations may encourage acceptance by clinicians (187), ensuring more reliable and ethical decision-making through validating the appropriateness of the suggested disorder (188). However, a systematic review found an overall lack of application of explainable AI in the context of AI-CDSS and, in particular, a lack of user studies exploring the needs of clinicians (188, 189). The adoption of algorithms can be hampered by their 'black box' nature. This means that they may perform well in terms of accuracy, but understanding the underlying processes used to achieve results can be difficult, even for experts.

One systematic review examined the impact of explainable AI (XAI) on clinicians' trust in AI-CDSS (190). While several studies found that clear and relevant explanations can increase trust, others reported no effect, and some noted that complex or confusing explanations reduced trust. Importantly, the review highlights that trust is not inherently beneficial, and that trusting incorrect outputs can harm clinical accuracy, while insufficient trust may lead to missed opportunities. These findings emphasise the need for careful design of XAI to support appropriate, calibrated trust in clinical settings.

A recent study proposed a pragmatic evaluation framework and found that while explanations can support trust and safety, they may also lead to confirmation bias, over-reliance, and cognitive burden (191). However, when tailored to clinical context, explanations helped reduce automation bias, supported uncertain decisions, and aided learning-positioning explainability as a useful tool beyond trust-building alone. Another study exploring an AI tool for sepsis treatment found that explanations boosted clinician confidence (192). Researchers have therefore begun developing a range of explainability methods to better support such interaction. Some of these approaches are discussed in the following section.

4.7.1 Saliency Maps

The current most popular approach for improving AI explainability in image interpretation in healthcare applications is to produce "saliency maps" (or "heatmaps"). These tools aim to highlight features in an input deemed relevant for the prediction of the presented model (193). The maps are designed with the aim of easy interpretation for a range of different users and may also help to detect and highlight unexpected behaviour (194). An earlier mentioned study by Bellemo et al (135) presented saliency maps for their algorithm in detecting DR (Figure 6).

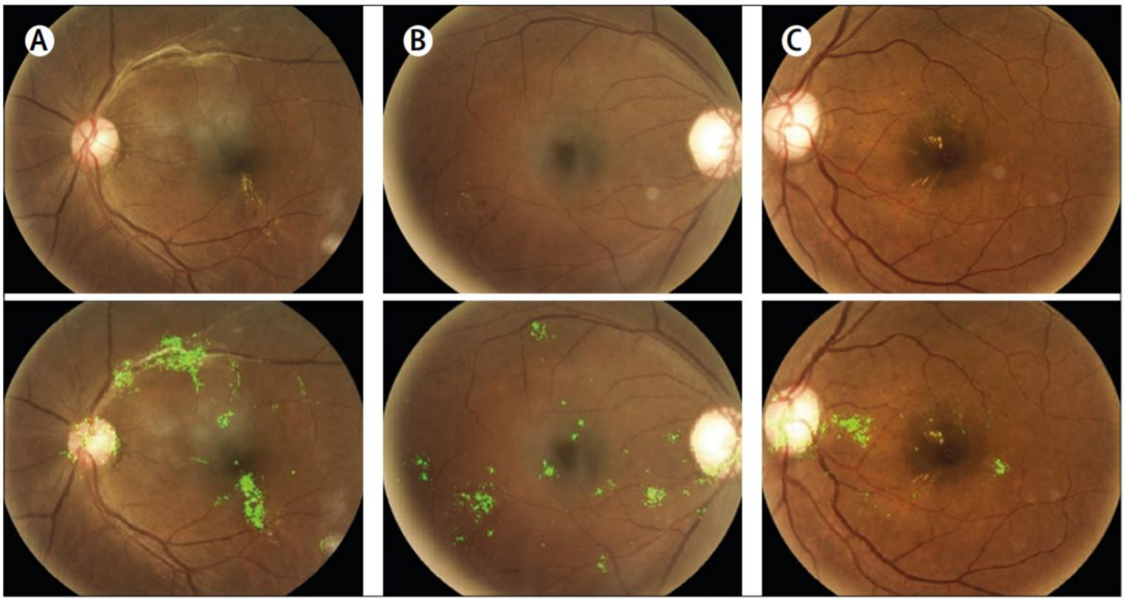

Figure 6: Heat map visualisations to highlight areas identified for demonstrating predicted referable diabetic retinopathy (DR). The green areas indicate the features which contributed to the artificial intelligence (AI) model's classification. These green areas may sometimes be missed by retinal graders due to poor image quality; thus heat-maps may aid clinicians when making a diagnosis. Used with permission (135).

Liu et al (195) developed and tested an algorithm for identifying glaucomatous discs using fundus images and presented their results using disc photographs along with their corresponding saliency maps. They found a correlation between the pattern of the saliency maps and the appearance of the discs. A more recent study by Hemelings et al (196) also assessed the potential of saliency maps in glaucoma diagnosis. They found that the maps indicated patterns of interest which were recurrent in the inferotemporal and superotemporal optic nerve head (ONH) ones. These heatmaps provided insights into the decision-making process made by the network when analysing the optic nerve image, acting as a method of explainability.

Although these saliency maps have demonstrated good potential, limited research has been carried out in the form of user studies to assess their use in practice. At the time of writing, as far as the author is aware, there are no published user studies assessing saliency maps in ophthalmology.

A recent online user study was designed to address a more general gap in research about the use of saliency maps (197), albeit not in the area of healthcare. This between-group study evaluated the use of saliency maps to aid understanding of a complex multi-label image classifier. Participants predicted the outcome of the classifier significantly more accurately when saliency maps were shown. Thus, the researchers reported that their results "*clearly indicate that saliency maps influenced our participants to notice the highlighted saliency features and to suggest that such features are important for the classification outcome*". However, this study used only a small number of image classes and only one specific network architecture to generate saliency maps. These methodological constraints may limit the applicability of the findings to those specific conditions. All participants also had a technical background and ML expertise was not controlled for, so the level of familiarity with the specific ML algorithms used in the study was unclear. Familiarity with how the systems worked may have affected the results.

4.7.2 Segmentation Maps

In ophthalmology research, another potential method of explainability has been developed for interpreting macular OCT scans (157). The Google-DeepMind AI algorithm is unique in that it splits the AI analysis of the OCT scan into two steps in order to account for inter-patient variability in disease presentation as well as differences in technical aspects of image processing. As part of the first step, a deep segmentation network is used to create a detailed device-independent tissue-segmentation map using 15 classes including anatomy, pathology and image artefacts. This network aims to not just indicate the features it has identified, but to clearly indicate where on the scan these features were picked up.

For the second step, a deep classification network analyses the segmentation map to produce diagnoses and one of four referral suggestions. After training on 14,884 labelled scans, the algorithm reached or exceeded the performance of 4 retinal specialists for a range of sight-threatening conditions. It has also demonstrated the ability to segment scan images obtained on different OCT devices.

Thus, the first step of segmentation offers a clear visualisation of the features detected by the algorithm, and when superimposed onto the OCT scans, may offer a clear visualisation of the AI's outputs. Again, HCI research is yet to be carried out on these outputs and their usability and interpretability require investigation.

4.7.3 HCI Research in Explainability

Recent HCI research has also focused on the use of AI for the interpretation of imaging outside a clinical context. These studies are important to consider as their findings may be applicable in a medical domain, such as considering how to present AI outputs to users in a way that is considered sufficiently explainable or interpretable. Cai et al. (2019) evaluated example-based explanations for a sketch-recognition algorithm and found that normative explanations (displaying training examples from that class) led to a better understanding of the system than comparative explanations (showing a comparison between the user's drawing and similar drawings from alternative classes) and increased the perceived capability of the system (198). Other researchers (199) have explored end-users' explainability needs and behaviours around AI explanations for bird classification, and found that participants desired practically useful information that can improve their collaboration with the AI.

One HCI study by Alqaraawi et al. (200) evaluated the use of saliency maps as a method of AI explainability to aid understanding of a complex multi-label image classifier. Participants predicted the outcome of the classifier significantly more accurately when saliency maps were shown. However, these post-hoc generated rationales of black-box predictions may not display the actual reasons behind predictions. They may offer deceptively simple explanations and have previously been cautioned against (201) due to the possibility of engendering a false sense of confidence in AI outputs (154, 202).

4.8 Summary

This chapter has examined the evolving role of artificial intelligence in healthcare, with particular attention to its application in optometry/ophthalmology and its integration into clinical decision support systems (CDSS). It reviewed AI application across ocular conditions such as diabetic retinopathy, glaucoma, AMD, and keratoconus, and outlined the emerging role of AI in OCT interpretation which is a key area of interest for this thesis. While AI systems demonstrate strong technical performance, their successful adoption in clinical practice depends on more than accuracy alone. Usability, explainability, workflow integration, and the human factors surrounding clinician interaction and trust are critical to their real-world effectiveness.

A recurring theme throughout this chapter is the importance of human-AI collaboration. Rather than replacing clinicians, AI should be designed to complement their expertise, enhance decision-making, and align with the cognitive and contextual demands of clinical work. However, over-reliance on AI, a risk posed by automation and anchoring biases, must be guarded against. Clinicians must develop a calibrated level of trust in AI systems, one that enables them to benefit from AI insights while retaining critical oversight and professional judgement.

This is particularly salient in the field of optometry, where research on clinician trust in AI remains limited. Existing studies suggest that optometrists are open to using AI tools, but trust is influenced by perceived reliability, relevance to clinical practice, and clarity about the tool's role as a support rather than a replacement. Notably, few studies have explored how optometrists engage with AI in the context of real-world tasks, particularly in the UK's primary care setting. There is also limited empirical evidence on how UK optometrists currently integrate OCT into everyday decision-making and how their information-seeking behaviours shape referral practice.

These gaps highlight the need for research that examines the lived experiences of optometrists, their responses to AI support, and the conditions under which such tools might be safely and effectively integrated. The following chapters address these gaps by investigating optometrists' information needs, their interactions with an example AI decision support in OCT interpretation, and the implications for designing human-centred AI-CDSS in primary eye care.

Chapter 5: Diagnostic Decisions of Specialist Optometrists Exposed to Ambiguous Deep-learning Outputs.

Parts of the following Chapter have been published in the following paper:

Carmichael J, Costanza E, Blandford A, Struyven R, Keane PA, Balaskas K. Diagnostic decisions of specialist optometrists exposed to ambiguous deep-learning outputs. Scientific Reports. 2024 Mar 21;14(1):6775.

5.1 Introduction

This chapter presents a reanalysis of results from a study that I originally conducted as part of my MRes project. During the PhD I revisited this dataset and applied different statistical techniques to gain new insights. The original study investigated how optometrists' diagnostic decisions were influenced by an AI-CDSS (157, 158) when presented with cases deliberately selected for their ambiguous or incorrect AI outputs. The reanalysis applied alternative statistical methods to reassess the impact of AI outputs on clinical decision-making, particularly in cases where the AI's diagnostic suggestions deviated from the reference standard. This method allowed for nonparametric analysis of interactions between variables, providing deeper insight into how AI influences diagnostic decisions. All statistical results reported in this chapter were new insights from this reanalysis. The case analysis presented in section 5.3.7 was also used in the MRes analysis to present examples of distinct matched sets with an obvious difference in responses between the 'AI diagnosis + segmentation' and the other two presentation formats.

This study utilised outputs from an ophthalmic AI-CDSS (157, 158) designed for the automated diagnosis of retinal disease. The system comprises two AI algorithms that analyse OCT scans to generate segmentation maps and multi-class diagnostic suggestions. Given the rarity of misclassifications, the analysis focused on cases where the AI's diagnostic outputs were either incorrect, as determined by disagreement with a reference standard, or ambiguous, where more than one diagnosis was proposed with high probability. This approach aimed to examine how users interact with AI outputs in two distinct scenarios: (a) instances where the AI's predictions were genuinely incorrect and (b) cases reflecting true clinical ambiguity in diagnosis. A third category was identified through a post hoc analysis of cases with large differences in diagnostic responses between the cases for matched presentation formats, highlighting instances where AI outputs appeared incorrect due to imperfections in the reference standard. The study further examined whether diagnostic decisions were influenced by the type of AI output presented, comparing diagnostic classification alone versus classification accompanied by segmentation overlays. Additionally, the level of trust placed in the AI outputs was assessed

5.2 Methods

5.2.1 Study Overview

Thirty clinical cases were assessed by 30 optometrists. For each case, participants were asked to choose the single most probable retinal diagnosis from ten options. They also chose their referral decision from four options (Figure 7) and indicated their confidence in their decision using a 5-point Likert scale. The primary analysis was focused on comparing optometrists' diagnostic decisions to the 'reference standard' clinical diagnosis for each case, as referral decisions post-diagnosis can be context-dependent (e.g., healthcare system, departmental protocols).The number of cases was limited by the effort and time the study required of participants, especially as it relied on clinicians participating in their own time without any incentive. Thirty cases per participant were considered as the maximum time that could be requested of them, estimating it would take them around 40-50 minutes (if they engaged in the assessment continuously).

For 10 cases ('no AI'), participants were provided with baseline information that included demographic and clinical characteristics (age, visual acuity, and biological sex), a colour retinal photograph and a full-volume macular OCT scan consisting of 128 B-scans or 'slices' (Figure 7). All OCT imaging was acquired using the Topcon 3D OCT-2000. The potential variability that might arise from using different OCT devices was not explored. Participants were able to 'scroll' through the 128 images using their arrow keys, allowing them to pause on any slices of interest. This closely mimicked their method of scrolling through macular OCT scans in real-world practice. A separate 10 cases were presented with baseline information plus the raw AI outputs for diagnostic classifications and referral probability (as a horizontal bar chart) ('AI diagnosis'). A further 10 cases were presented with baseline information, the diagnostic classification output and, additionally, the segmentation output of the AI algorithm - i.e., a colour-coded overlay highlighting clinical features within each of the OCT 128 B-scans (‘AI diagnosis + segmentation’). This segmentation output was scrolled through sequentially with the corresponding 128 OCT slices. The methods of displaying the raw outputs from the model were based on a mock visualisation used in the original validation paper which has not been validated as an optimal method of displaying outputs. This visualisation consisted of an average segmentation map calculated from the results of five hypotheses from a segmentation network. Two different types of presentation format were chosen (i.e., AI support with and without segmentation maps) as these two formats may affect diagnostic decisions differently. Diagnostic outputs encompass a constellation of potential imaging features on OCT that should and/or could be present to inform the clinical diagnosis. A segmentation output highlights the presence or absence of specific pathological imaging features on OCT (which feed into the diagnostic model to inform its prediction), but these features could be present in more than one retinal diagnosis. After completing each set of 10 cases with AI information (‘AI diagnosis’ and ‘AI diagnosis + segmentation’), participants recorded their level of trust in the AI outputs using a 5-point Likert scale.

The research adhered to the tenets of the Declaration of Helsinki. All patient information, images and scans were used in line with Research Ethics Committee (REC) approval (20/HRA/2158). Data acquired from study participants was in line with UCL interaction centre Research Ethics Committee approval (UCLIC/1819/006/BlandfordProgrammeEthics).

5.2.2 Choice of Cases

The 30 cases used data and AI analysis generated as part of a published study(157) The original validation dataset comprised anonymized scans from n=997 patients with a range of retinal diseases who attended MEH between 1 June 2012 and 31 January 2017. Images with poor quality and/or significantly reduced signal strength were excluded.

Cases were chosen by JC to cover a range of macular pathologies and to include healthy scans (Appendix 2). When choosing cases, the diagnoses suggested by the AI were compared to the 'reference standard' clinical diagnosis, decided by an ophthalmologist during a face-to-face examination. The cases were matched across the three presentations to participating optometrists with respect to 'reference standard' diagnosis and difficulty. The cases were purposely chosen to include a disproportionately large number of instances where the AI disagreed with the ‘reference standard’ (20% of cases) or was ambiguous (40% of cases) as the focus was on interesting cases whereby incorrect/ambiguous AI may influence participants' decisions and were aiming to inflate the number of incorrect/ambiguous outputs while retaining some resemblance to a real-life case-mix. Fifty per cent of cases were determined by a consultant ophthalmologist and medical retina specialist (KB) as also being truly clinically ambiguous based on the OCT findings. The remaining 40% of cases were considered unambiguous with the AI diagnosis agreeing with the 'reference standard'. The actual incidence of cases where the AI diagnosis disagrees with the reference standard or provides uncertain outputs is much smaller than in this study. When assessing the sensitivity and specificity of the AI diagnosis for all assessed conditions, using receiver operating characteristic curve (ROC) diagrams, the area under the curve (AUC) was reported as between 96.63 (for epi-retinal membrane) and 100.00 (for full-thickness macular hole) in the original validation study of the AI-CDSS (157). No information about AI accuracy was provided to participants until debriefing.

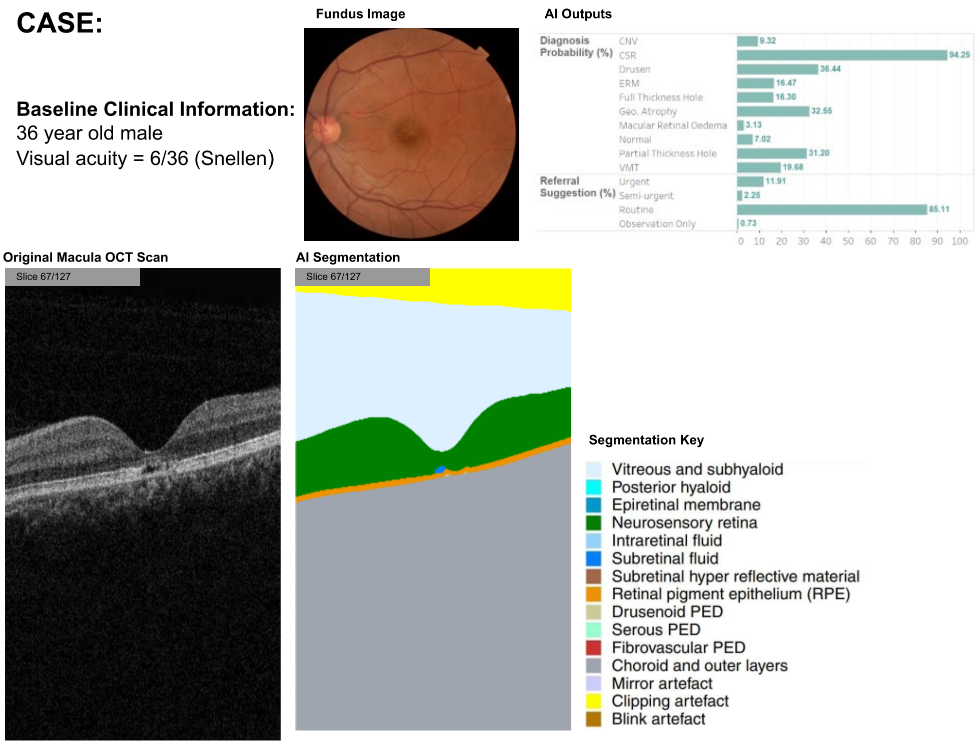

Figure 7: Elements shown during clinical case review. The example includes baseline information, AI diagnosis suggestions, and segmentation overlays; other cases included only a subset (e.g., AI diagnoses only).

5.2.3 Study Set Up

An online survey tool was used for submitting responses. A HTML case viewing interface (Figure 7) was accessible only by study participants and investigators within the MEH network. Basic training about the AI segmentation overlays and diagnostic outputs was provided to ensure all participants had a similar level of understanding (Appendix 2).

5.2.4 Participants

Thirty qualified optometrists were recruited; all worked at MEH and none had previous exposure to the AI-CDSS. Half of the participants were recruited to fit predetermined criteria of 'more experienced', and half 'less experienced' (Supplementary Figure 3). These group allocation criteria were decided with a Medical Retina (MR) Consultant (KB), based on experience in a MR clinic, which was used as a surrogate for familiarity with interpreting OCT scans. No minimum number of years' experience was required. Informed consent was obtained from participants via an online form prior to beginning the survey.

Each participant was randomly allocated to one of three groups, with each group experiencing all three presentation formats in a different order (balanced through a Latin square). This counterbalanced order was to control for presentation order as a possible confounding factor influencing results (Figure 8). Each group contained five more experienced optometrists and five less experienced ones. All 30 optometrists saw each of the 30 cases.

5.2.5 Statistics

Quantitative analysis was conducted in SPSS for Windows version 28 (SPSS Inc, Chicago, IL, USA) and the Windows aligned rank transform (ART) open-source application (203). ANOVA was used to test for a significant difference between categorical groups post ART adjustment. A p value of <0.05 was considered statistically significant. Where multiple post-hoc pairwise comparisons were performed, Bonferroni-adjusted p-values were reported.

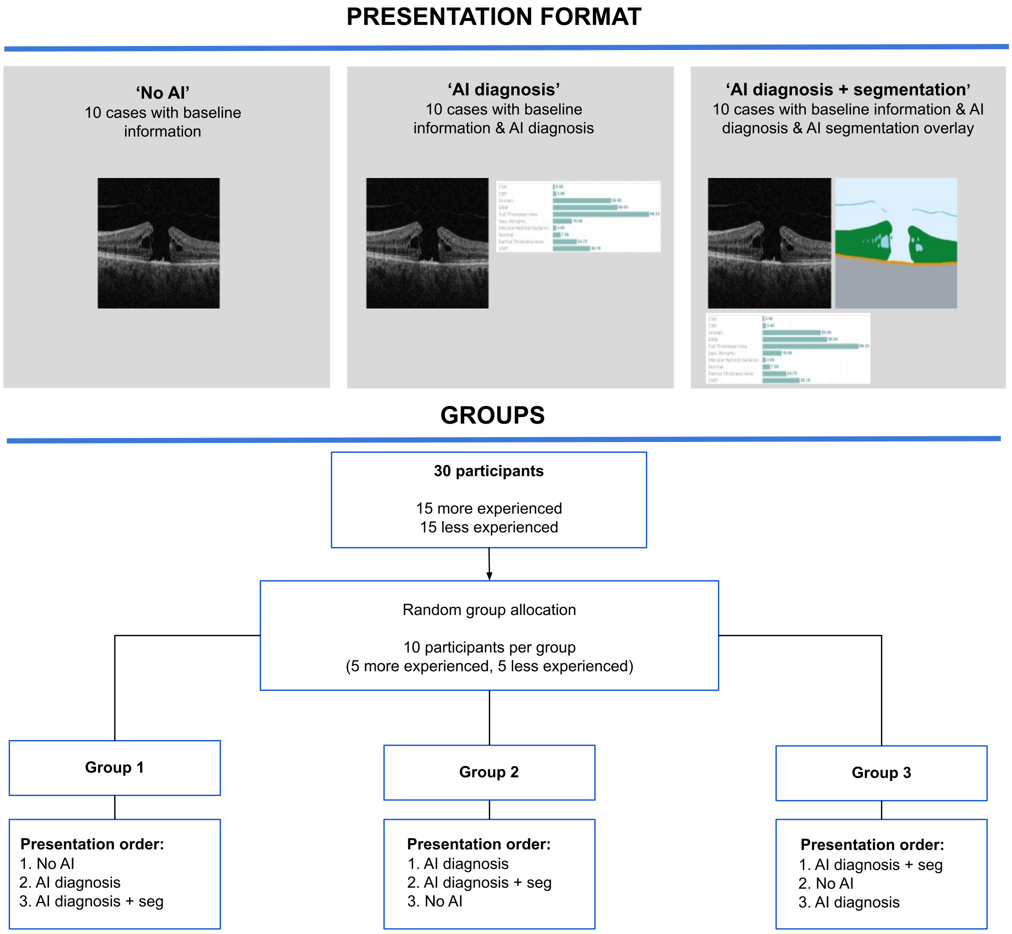

Figure 8: Order of Case Presentation. Participants were randomly assigned to one of three groups. Each group viewed the clinical cases in a different order to account for possible order effects on responses and contained five more experienced participants and five less experienced participants.

5.3 Results

5.3.1 Diagnostic responses

Each of the 30 participants answered diagnostic questions for 30 cases, resulting in 900 responses in total. The median completion time taken to complete the 30 cases was 44 minutes, 50 seconds. Completion time varied widely between participants (range: 16 minutes, 29 seconds to 182 minutes, 56 seconds), suggesting some participants completed the study while multitasking. Indeed, prior work pointed out that multitasking is common for participants of online studies (204). Thus, further analysis of task completion time would be of limited value. An ANOVA with ART adjustment revealed significant differences in reference standard-aligned responses across the three presentation formats (p<0·001) (Table 17). A borderline effect of the order of case presentation was also found (p=0·049). There was no significant effect of experience on the number of reference standard-aligned responses. When testing interactions between reference standard-aligned responses and potential confounding factors, a significant interaction with order and presentation format was found. All other interactions showed no significant effect.

	Diagnosis	
Factor(s)	**F-value**	**p-value**
1 Experience	1·426	0·244
2 Order	3·195	**0·049***
3 Presentation format	15·036	**<0·001***
4 Experience: Order	2·046	0·140
5 Experience: Presentation	1·877	0·164
6 Order: Presentation	2·903	**0·032***
7 Experience:Order:Presentation	1·400	0·280

* p values considered statistically significant

Table 17: Results from ANOVA testing on number of diagnoses in agreement with the reference standard. ANOVA performed on results using aligned rank transform (ART). Results for factors 1-3 represent the effect of a single factor on diagnosis. Results for factors 4-7 represent the effect of two or more factors interacting. Values in bold represent statistically significant results.

5.3.2 Effect of presentation format

The participants' responses were divided into 3 classes, based on the presentation format. In the 'no AI' group, 242/300 (81%) responses agreed with the reference standard. In the 'AI diagnosis' group, 224/300 (75%) agreed with the reference standard. In the 'AI diagnosis + segmentation' group, 204/300 (68%) agreed with the reference standard. Significant differences in responses agreeing with the reference standard were found between all 3 pairs using Bonferroni-adjusted post-hoc pairwise comparisons: 'no AI' vs 'AI diagnosis' (p=0·049) [became non-significant when excluding the results from the 3 cases of Epiretinal Membrane (ERM). See supplementary analysis in Appendix 2], 'no AI' vs 'AI diagnosis + segmentation' (p<0·001) and 'AI diagnosis + segmentation' vs 'AI diagnosis' (p=0·011).

5.3.3 Effect of case order

A post-hoc assessment within groups, using Bonferroni-adjusted post-hoc pairwise comparisons, (Figure 9) revealed a significantly higher number of responses agreeing with the reference standard when comparing the first set of 10 cases viewed vs the third (p=0·041). No significant differences were found between the first set of 10 cases viewed vs the second (p=0·771) or the second vs the third (p=0·514).

5.3.4 Interaction between presentation format and case order

When making post-hoc comparisons, using Bonferroni-adjusted post-hoc pairwise comparisons, (Figure 9), there was a significant difference in responses agreeing with the reference standard between 'no AI' presentation viewed first vs third (p=0·035) and between 'AI diagnosis' presentation viewed second vs third (p=0·018). No other comparisons were significant.

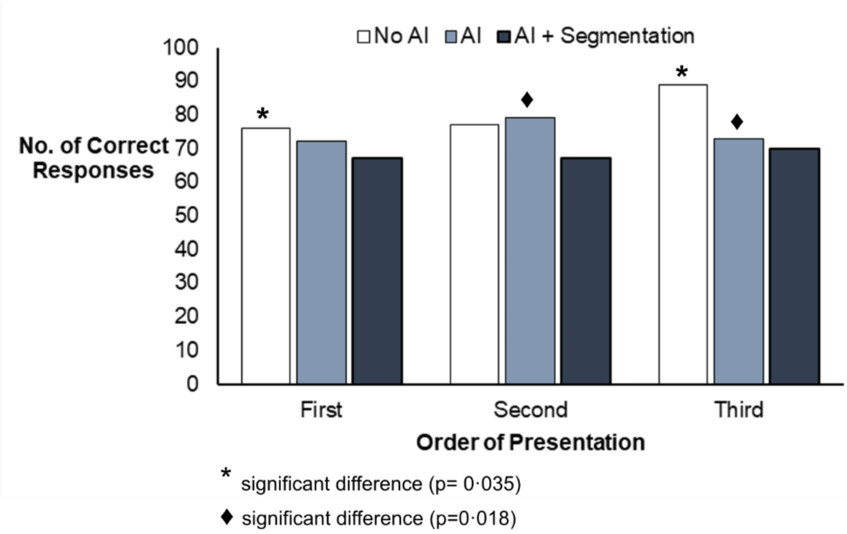

Figure 9: Number of 'correct' diagnostic responses for three presentation formats, based on the order they were viewed by participants. Post-hoc comparisons were carried out for the presentation formats.

5.3.5 Participants' level of agreement with AI

When assessing agreement with AI outputs, there was a significant effect of presentation format (p=0·001) (Table 18). There was no significant effect of experience (p=0·080) or presentation order (p=0·816) and no significant interactions.

	Agreement	
Factor(s)	**F-value**	**p-value**
1 Experience	0·065	0·080
2 Order	0·216	0·816
3 Presentation Format	11·890	**0·001***
4 Experience: Order	1·148	0·326
5 Experience:Presentation	0·790	0·391
6 Order:Presentation	0·260	0·772
7 Experience:Order:Presentation	1·058	0·355

* p values considered statistically significant

Table 18: Results from ANOVA testing on number of responses in agreement with AI outputs. ANOVA performed on results using aligned rank transform (ART). Results for factors 1-3 represent the effect of a single factor on agreement with AI. Results for factors 4-7 represent the effect of two or more factors interacting. Values in bold represent statistically significant results. *p-value statistically significant

5.3.6 Effect of presentation format on agreement with AI

To compare the level of agreement with 'correct' AI diagnosis for responses given with and without segmentations, the responses were divided into four groups, based on the participant being ‘correct’/’incorrect’ and the AI being ‘correct’/’incorrect’. For the 70% of cases where the AI diagnosis agreed with the reference standard, an ANOVA with ART correction revealed that participants agreed with the AI diagnosis significantly more when segmentation was not displayed (p<0·001, Table 19). In contrast, for cases where AI diagnosis disagreed with the reference standard (30%) no significant effect of segmentation display on agreement with AI diagnosis was found (p=0·236).

A) AI Diagnosis

	AI Correct	AI Incorrect	
Participant Correct	**199 (66%)**	25 (8%)	Total 224(75%)
Participant Incorrect	**11 (4%)**	*65 (22%)	Total 76(25%)
	Total 210(70%)	Total 90(30%)	

* In 58/65 incorrect responses, the participant and AI gave the same 'incorrect' diagnosis.

B) AI Diagnosis + Segmentation

	AI Correct	AI Incorrect	
Participant Correct	**174 (58%)**	30 (10%)	Total 204(68%)
Participant Incorrect	**36 (12%)**	*60 (20%)	Total 96(32%)
	Total 210(70%)	Total 90(30%)	

*In 53/60 incorrect responses, the participant and AI gave the same 'incorrect' diagnosis.

Table 19: Total participant responses for diagnostic decisions divided into four categories based on being 'correct'/'incorrect' and in relation to AI diagnosis being 'correct'/'incorrect'. A) represents the responses provided for cases where AI diagnoses were displayed (N=300). B) represents the responses provided for cases where AI diagnosis plus segmentation overlays were displayed (N=300). Numbers highlighted in bold represent a significant difference in 'correct' participant responses between A) and B) (p<0·001 with ART and ANOVA analysis).

5.3.7 Case Analysis

To explore the reduced agreement with AI diagnosis when segmentation overlays were displayed, a post-hoc was completed by assessing matched cases, with respect to diagnosis and difficulty, across the presentation formats, and identified two distinct sets with an obvious difference in responses between the ‘AI diagnosis + segmentation’ and the other two presentation formats. The following two examples are particularly informative.

Set 1

For set one, the reference standard and AI diagnosis was 'normal', which 29 and 28 participants agreed with in the ‘AI diagnosis’ and ‘no AI’ presentations respectively. However, in the AI diagnosis + segmentation format, 23 optometrists agreed with the reference standard and AI diagnosis, while seven diagnosed an epiretinal membrane (ERM), prompted by small areas of ERM identified in the segmentation (Figure 10).

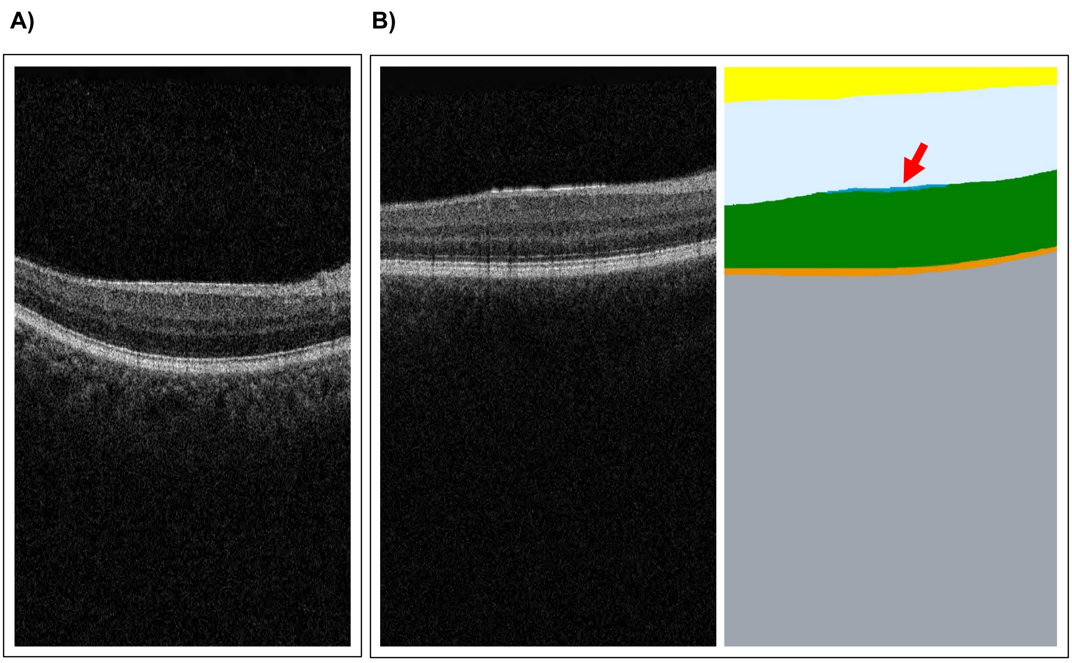

Figure 10: One image taken from two matched OCT scans. A) OCT presented with AI diagnosis. B) OCT presented with AI diagnosis plus segmentation. Very similar areas of hyper-reflectivity are present, which for B) was identified as an epiretinal membrane (ERM) by the segmentation overlay (dark blue area, indicated by red arrow; arrow not shown to participants). Both A) and B) were classified as normal by the AI diagnosis.

Set 2

In this case the AI diagnosis was dry macular degeneration in agreement with the reference standard, which 29 participants also diagnosed for the ‘no AI’ and ‘AI diagnosis’ presentations. However, the segmentation identified possible areas of intra-retinal fluid overlying atrophy (corresponding to pseudocysts) and adjacent posterior epithelial detachment (PED) on the OCT, probably prompting 11 participants to diagnose the patient with choroidal neovascularisation (CNV, wet AMD) in the ‘AI diagnosis + segmentation’ presentation (19 diagnosed as dry AMD) (Figure 11).

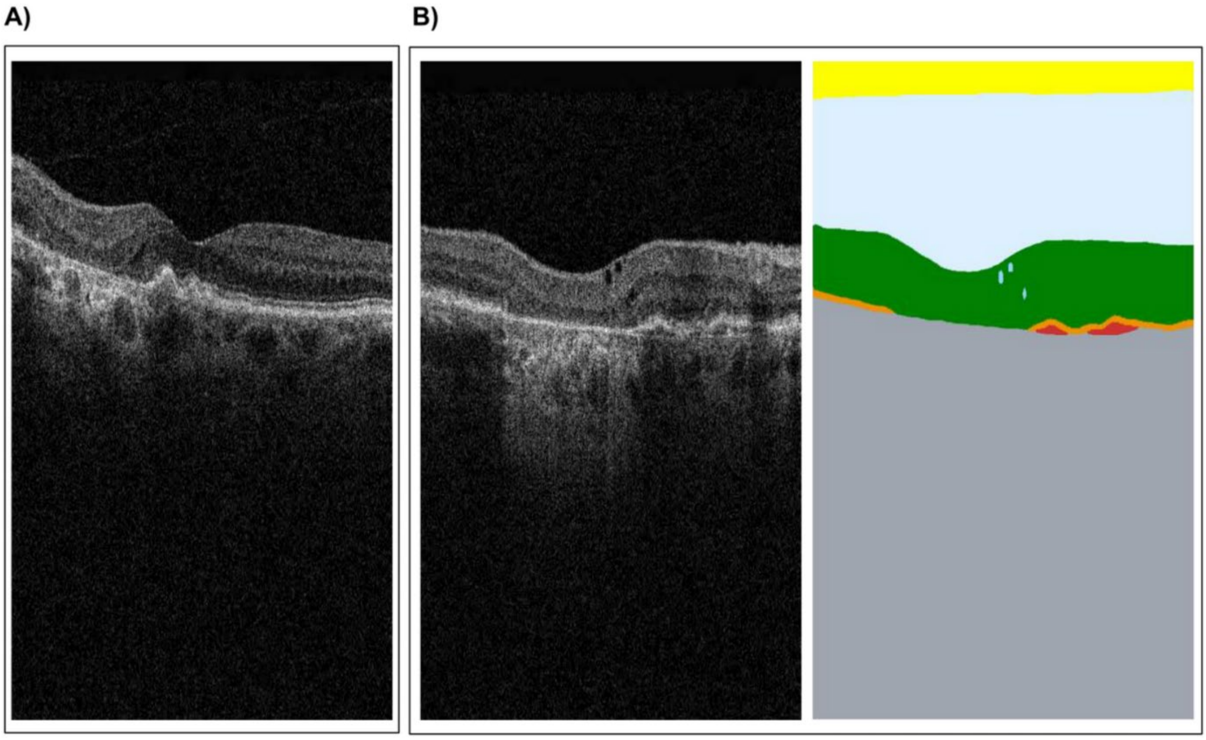

Figure 11: One image taken from two matched OCT scans. A) OCT presented with AI diagnosis. B) OCT presented with AI diagnosis plus segmentation. Similar areas of geographic atrophy with overlying minimal pockets of intra-retinal hypo-reflective spaces are present which for B) were identified as intra-retinal fluid by the segmentation overlay (light blue pockets). In both cases there are adjacent PEDs to the atrophic areas, more marked in case A). Both A) and B) were classified as having features of dry macular degeneration (geographic atrophy and drusen) by the AI diagnosis.

5.3.8 Reported diagnostic confidence.

Overall, the more experienced participants were significantly more confident with their diagnoses than less experienced participants (p=0·012) (Table 20, Figure 12).

No significant effect was found across the 3 groups based on presentation format (p=0·461), order (p=0·360) or any interaction between factors.

	Confidence	
Factor(s)	**F-value**	**p-value**
1 Experience	7·429	**0·0118 ***
2 Order	1·022	0·360
3 Presentation	0·774	0·461
4 Experience: Order	0·351	0·704
5 Experience: Presentation	1·315	0·269
6 Order: Presentation	1·014	0·406
7 Experience:Order:Presentation	0·902	0·468

* p values considered statistically significant

Table 20: Results from ANOVA testing on diagnostic confidence indicated by participants using a 5-point Likert scale. ANOVA performed on results using aligned rank transform (ART). Results for factors 1-3 represent the effect of a single factor on diagnosis, confidence and trust. Results for factors 4-7 represent the effect of two or more factors interacting. Values in bold represent statistically significant results.

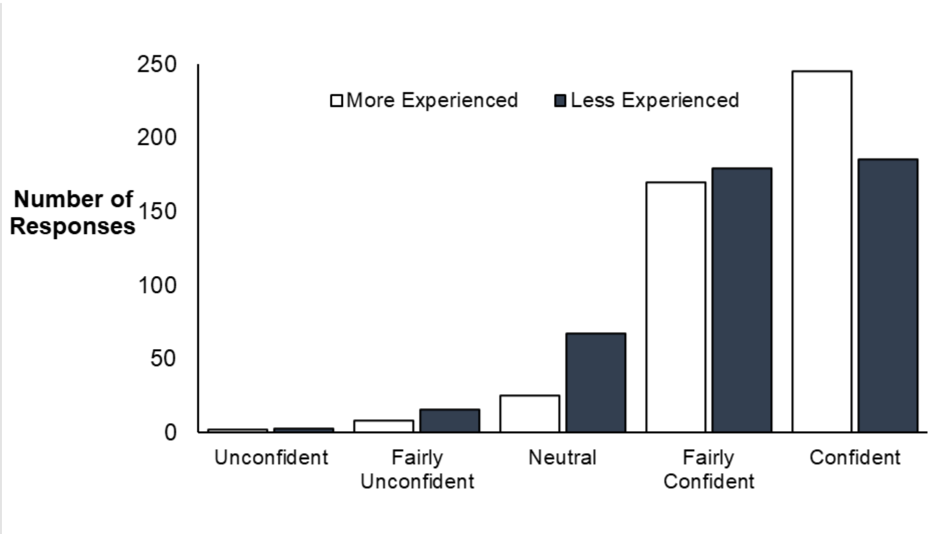

Figure 12: Total responses for diagnostic confidence (n=900), divided into levels of experience (n=450 more experienced, n=450 less experiences). A significant difference in responses for confidence was found (p=0·012) between the two groups based on experience, with more experienced participants overall more confident in their diagnostic decisions.

5.3.9 Reported trust in AI

An ANOVA with ART adjustment revealed that participants trusted the AI significantly more when segmentation overlays were displayed compared to not (p=0·029) (Table 21, Figure 13). The less experienced participants reported a significantly higher level of trust compared to more experienced participants (p=0·038). The case order had no significant effect on reported trust (p= 0·582). There was a significant interaction between level of experience and order (p=0·049); however, there was no trend when using Bonferroni-adjusted post-hoc pairwise comparisons. No other significant interactions between factors were found.

	Trust	
Factor(s)	**F-value**	**p-value**
1 Experience	4·842	**0·038***
2 Order	0·548	0·582
3 Presentation	5·395	**0·029***
4 Experience: Order	3·227	**0·049***
5 Experience: Presentation	1·082	0·309
6 Order: Presentation	3·184	0·053
7 Experience: Order:Presentation	1·705	0·197

* p values considered statistically significant

Table 21: Results from ANOVA testing on level of trust in AI outputs indicated by participants using a 5-point Likert scale. ANOVA performed on results using aligned rank transform (ART). Results for factors 1-3 represent the effect of a single factor on trust in AI. Results for factors 4-7 represent the effect of two or more factors interacting. Values in bold represent statistically significant results.

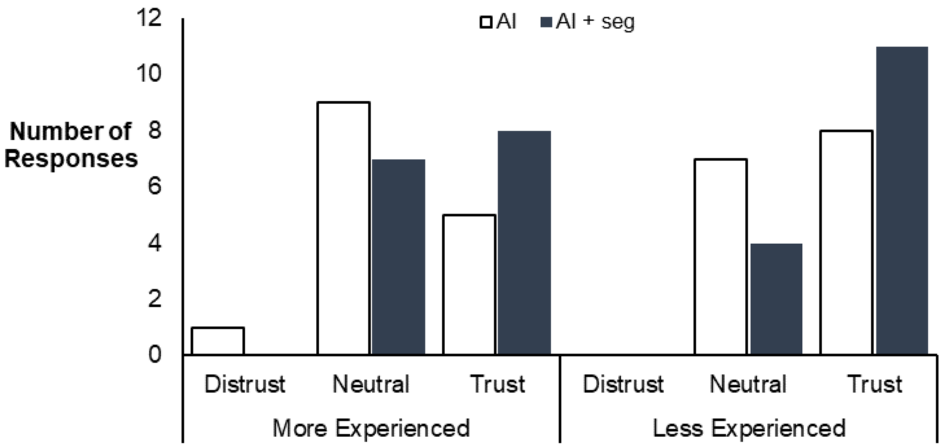

Figure 13: Total responses for level of trust (n=60), divided into level of experience (n=30 more experienced, n=30 less experienced). A significant difference in responses for trust was found between the two groups based on experience (p=0·038), with more experienced participants overall more confident in their diagnostic decisions. Significantly more participants trusted the AI plus segmentation overlays (AI + Seg) over the AI outputs alone (p=0·029).

5.4 Discussion

This study explored the impact of introducing an AI-CDSS on diagnostic decisions made by hospital optometrists when interpreting OCT scans and expands on previous studies in other areas of medicine which have demonstrated a positive effect of human-AI collaboration when using a system of high diagnostic accuracy (2, 205); however, unlike previous work a high proportion of cases (60%) were selected for which the outputs of the AI system were incorrect (disagreed with the reference standard) or were ambiguous (more than one diagnosis proposed with high probability).

Overall, the participants made the most accurate diagnoses with respect to the reference standard when assessing the clinical cases without AI diagnostic support. This 'no AI' accuracy of 81% was very similar to the 80% mean diagnostic accuracy found by Jindal et al (12), where optometrists assessed retinal and optic nerve OCTs to determine whether either were 'diseased'. The number of 'correct' responses decreased to 75% when AI diagnosis was presented. Cases were deliberately selected based on AI outputs because, though infrequent, the study aimed to explore how incorrect (whether stemming from a truly incorrect AI diagnosis or a disagreement with an imperfect reference standard) or uncertain AI diagnostic support may affect human diagnostic performance. A recent study by Tschandl et al (2) reported a negative effect of incorrect AI outputs on participants' diagnostic accuracy. That study, however, arbitrarily modified the output of an AI system to artificially produce incorrect results. The focus of this study was on the (rare) actual cases where the AI system produced output inconsistent with the reference standard which does not automatically equate with incorrect output.

Even fewer diagnostic responses agreed with the reference standard when both AI diagnosis and AI segmentation were displayed (68%). The role of clinically ambiguous cases is likely to be the fundamental factor leading to this result. Cases where participants may have based their decisions on innocuous, subtle details revealed on the segmentation overlays rather than the AI diagnosis may offer an interesting and informative perspective on Human-AI interaction. Although the reference standard and the AI diagnosis were aligned in the examples identified, an alternative interpretation of the imaging in favour of an ERM being present (for set 1) and a CNV diagnosis (for set 2) could conceivably be made even by ophthalmology specialists.

These findings also highlight a conundrum on the value of presenting segmentation overlays to provide more information to clinicians, especially those less experienced in the interpretation of OCT scans. The diagnostic classification algorithm was trained on the segmentation produced by the segmentation algorithm; however, it was trained using clinical labelling of segmentations by experts at MEH, who were able to differentiate nuanced presentations of pathological OCT features highlighted by the segmentation algorithm in the broader context of each case. This creates different thresholds for pathology detection 'reference standards' and thus discrepancies between the segmentation and diagnostic outputs. For any AI systems in healthcare, a clear distinction is required between levels of ‘detectable’ and ‘clinically significant’ pathology and one must be careful when showing visualisations of intermediate stages to users, as they may be misinterpreted. Considering also the positive effect that the visualisations had on participants' trust, the effect of the segmentation overlays observed in this study suggests it is important for any additional visualisation to be aligned with the AI diagnostic output.

There were no significant differences between the number of correct responses from the two groups based on level of experience. This is contrary to findings of a previous study in ECG interpretation using a non-AI system (206). However again results can be compared to the findings of Tschandl et al (2), whose diagnostic task was similar to the one in this study, in that it used multi-class outputs and an AI-CDSS. That study found an inverse relationship between the net gain from AI-based support and participant experience for an accurate AI system. The combined findings suggest that less-experienced participants may benefit most from correct AI diagnostic support, but all users are equally influenced by incorrect outputs.

In this study, AI did not increase optometrists' diagnostic confidence, either with or without segmentation overlays. Bond et al (206) reported that incorrect automated diagnostic support significantly reduced interpreters' confidence. Despite the selection of 60% of cases where the AI was ‘incorrect’/ambiguous’ there was still no significant impact on diagnostic confidence for the full cohort. Future research should assess diagnostic confidence using the AI with its true diagnostic accuracy for clinical implementation (157).

While AI in ophthalmology offers great potential, the social and legal challenges cannot be ignored. Reliability and accountability of the AI systems and their impact on clinical decision-making creates a complicated dynamic with healthcare professionals. For AI to be accepted by clinicians, both personally and institutionally, the systems must be reliable and trusted (207). In this study, only one participant reported that they distrusted the AI diagnoses (without segmentation), with 16 neutral and 13 trusting. Given the case selection, it would have been possible to inadvertently introduce a bias against the system. Dietvorst et al (159), describe this as 'algorithm aversion', which is the reluctance to use algorithms known to be imperfect. Participants may detect the AI’s imperfect accuracy and uncertainty and calibrate their trust (208) based on this isolated experience of using the AI.

Another challenge of introducing AI into clinical practice is the well-known "opaque box" problem (207), describing many AI systems as non-transparent. Even though the accuracy of the AI was matched between the ‘AI diagnosis’ and ‘AI diagnosis plus segmentation’ presentations, the increased transparency with the segmentation overlays may have created the significantly higher level of trust in the AI when segmentations were displayed. This finding was particularly interesting in this study as although there was increased trust in the system when segmentations were displayed, participants agreed less on average with the AI diagnosis and reference standard in this presentation format. Further research is required to explore how different elements of AI visualisations are utilised during clinical decision-making and which aspects most influence clinicians' OCT interpretation.

5.4.1 Limitations

Four main limitations to this study were identified. Firstly, because the study was run remotely it was not possible to observe participants' decision-making processes. Future research with observations and/or detailed exit interviews would provide valuable insights into participants' interactions with AI systems. Although the remote set up allowed clinicians to complete the study at a time and pace that was convenient to them, it meant that statistical analysis on the time taken for clinicians to review cases with and without AI support could not be studied. Analysis of review time would be an interesting focus for future study.

Secondly, the AI segmentation model was trained by human graders who annotated thousands of OCT slices for features of ocular pathology based on grading protocols. Such protocols mandated the annotation of any trace of features such as ERM even if not clinically significant. In such cases of trace ERM, both ‘ERM’ and ‘normal’ can be considered an acceptable diagnosis based on the different thresholds for detectable vs clinically significant pathology. In comparison, the reference standard clinical diagnosis would typically only diagnose pathology such as ERM if it was considered clinically significant. As a result, the classification of both AI and participant diagnostic decisions into ‘correct’ and ‘incorrect’ compared to the reference standard is occasionally ambiguous.

The study involved matching across the three study conditions based on clinical case selection. Although the matched cases were confirmed by a medical retina specialist (KB) the individual cases are unique and that it would be impossible to find identical cases when matching for AI outputs, OCT appearance and clinical information. Finally, while the aim was to maximise the ecological validity of the study, it was limited in both not reflecting a natural mix of cases and including less patient information than would normally be available.

5.4.2 Influence on Future Studies

The findings from the reanalysis were documented for submission to *Scientific Reports*. During the manuscript preparation process, engagement with key stakeholders, including Google employees and senior clinicians involved in the development of the AI algorithms studied, provided valuable insights into the Moorfields-Google-DeepMind AI model and its diagnostic outputs. This deeper understanding has informed the direction of subsequent chapters. Given the influence of these insights, it is essential to reflect on the key lessons learned:

1. *Diagnostic Output Percentages Are Not Directly Comparable*
   Since the AI assesses each condition independently, the probability values assigned to different conditions are not designed to be compared directly. For example, a 60% probability for Condition A versus 90% for Condition B does not imply that Condition B is more likely. Both conditions are simply considered present if their probability exceeds the 50% threshold. This calls into question the case selection method used in the MRes study, which was based on comparing probability outputs across conditions.

2. *Limitations of the 'Reference Standard'*
   In the MRes study, participant responses were compared against clinical diagnoses made during face-to-face consultations at Moorfields Eye Hospital, which served as the reference standard. However, upon reviewing selected cases with KB, an experienced consultant ophthalmologist, it became clear that certain cases were open to interpretation and did not have a single, definitive diagnosis. This highlights the complexity and inherent ambiguity in clinical assessment, particularly in the interpretation of OCT scans. As a result, instances where participant or AI diagnoses diverged from the reference standard may reflect reasonable alternative interpretations rather than outright errors.

3. *Distinguishing Detectable vs. Clinically Significant Pathology*
   Some cases in the study revealed a discrepancy between pathology identified by AI-generated segmentation maps and the diagnostic outputs. For example, a minimal epiretinal membrane may be detected by the segmentation map but not classified as ‘present’ by the diagnostic algorithm if its probability does not

exceed 50%. In such cases, the clinical reference standard may label the scan as ‘normal,’. If AI visualisations of intermediate stages are introduced into clinical practice, users must be trained to interpret them appropriately. Currently, optometrists rely on personal experience to determine clinical significance, but new measurement approaches may shift decision-making toward more standardised criteria

5.4.3 Conclusions

The three lessons outlined in this chapter have significantly deepened my understanding of the Moorfields-Google-DeepMind model, particularly the complexities involved in determining how AI outputs should be presented to users. While algorithmic transparency is often emphasised, the way certainty levels and probabilities are displayed requires careful consideration. Presenting all probabilities for all conditions may be misleading, as users might mistakenly compare them across conditions rather than interpreting them independently. To address this, the interview study described in Chapters 6 and 7 adopts a simplified approach, presenting diagnostic outputs based on whether the algorithm’s confidence exceeds a 50% threshold. This decision was informed by the insights gained from the lessons discussed.

Additionally, these lessons underscore the importance of user onboarding before system implementation. Providing clear, appropriately detailed explanations of the AI system’s functionality is essential for ensuring its effective and responsible use in clinical practice. If AI decision-support systems (AI-CDSS) are to be integrated into ophthalmological assessments, they must be used in a way that aligns with clinical reasoning rather than being overly relied upon.

The study’s case selection, deliberately including instances where the AI-CDSS was incorrect or uncertain relative to the reference standard, revealed an interesting effect on diagnostic decisions. Regardless of experience level, optometrists' agreement with the reference standard was lowest when segmentation overlays were presented. Although segmentations often highlighted true anatomical abnormalities, these were sometimes clinically insignificant, leading to disagreements between participants, the AI, and the reference standard. This pattern of disagreement raises important questions about the validity of the reference standard itself, particularly in borderline cases requiring nuanced clinical judgment. Despite the reduced agreement, participants tended to place greater trust in the AI when segmentations were visible, possibly due to the perception of increased transparency.

In Human-AI interaction research, quantified analyses provide valuable insights. However, this study highlights the complexity of clinical interpretation, the limitations of reference standards, and the distinction between detecting abnormalities on imaging versus diagnosing clinically significant disease. These factors caution against drawing absolute conclusions about AI-CDSS impact based solely on numerical assessments. Instead, this work points to the need for further mixed-methods research to explore the cognitive processes underlying AI-assisted decision-making and to better understand how AI-CDSS influence clinical judgments in practice.

Chapter 6. In-Depth Interview Study with Primary Care Optometrists

6.1 Introduction

As previously discussed, in recent years, there has been a dramatic increase in the use of advanced ocular imaging in UK optometric primary care (11). Overall, the increased availability of OCT imaging in primary care is positive, as it provides valuable additional data to aid diagnoses and can help detect early disease. However, optometrists' level of training in OCT imaging is varied across primary care. The systematic review as reported in Chapter 2 found no studies assessing the possible effect of increased OCT imaging on the number of false-positive referrals from primary care optometrists; however it is thought that in some cases, clinicians may lack the experience required to confidently interpret OCT findings independently and benign changes detected on imaging may be misinterpreted and referred unnecessarily.

Recognising a need for support, apps such as Pando (Forward Clinical, UK) (209) have been developed and are being trialled as secure and confidential communication channels between healthcare professionals. Specsavers Opticians also provide their own internal forums via GDPR compliant messaging apps such as 'Yapster' for discussions between their optometrists. Additionally, social media apps may be used by some optometrists as convenient communication tools for timely responses to clinical queries. Official advice from NHS information governance to all medical professionals is that it is fine to use such apps when "there is no practical alternative and the benefits outweigh the risks" (210). The College of Optometrists (CoO) offers similar advice specifically for optometrists (211) with additional guidelines for the sharing of identifiable patient information. However, advice overall remains vague, and other more secure ways of accessing clinical support would be preferable.

As discussed, AI offers a potential means of addressing the limitations of existing diagnostic and management decision support available to optometrists. To gain a deeper understanding of their information needs when faced with challenging or ambiguous retinal OCT cases, in-depth semi-structured interviews were conducted with primary care optometrists. These interviews explored their current sources of clinical support and the reasons for their preferences, as well as their views on the potential role of AI-based clinical decision support tools. To facilitate discussion, participants were shown example outputs from the prototype system developed by Moorfields and Google DeepMind as used in the study discussed in Chapter 5.

6.1.1. Objectives

The interview study was designed to address several of the research questions outlined in Section 1.2, focusing on both current clinical practice and the potential role of AI-based decision support. The following specific objectives were developed to guide the analysis. Together, they address research questions 3 to 7, either fully or in part. Each research question is addressed by at least one objective (Table 22), and in most cases by multiple objectives.

Objectives

1. To explore optometrists' experiences of using OCT and other advanced imaging in primary care practice.
2. To investigate whether, and from which sources, optometrists seek information when faced with challenging clinical cases, with a particular emphasis on retinal conditions.
3. To examine why certain sources of clinical support or information are preferred over others.
4. To explore optometrists' views on the potential role of AI support tools in diagnosing retinal conditions.
5. To identify what information optometrists would ideally want from a clinical decision support tool, particularly in cases of suspected retinal conditions considered ambiguous by consultant ophthalmologists.
6. To investigate how and when information from an AI-CDSS should be presented to support decision-making without disrupting clinical workflows.

Research Question	Related Objective(s)
RQ3. How do optometrists experience and use OCT imaging in their day-to-day clinical practice, particularly in the management of patients with suspected retinal disease?	Objective 1
RQ4. Where do optometrists currently seek information or support when faced with clinical uncertainty regarding OCT findings, and why are sources favoured?	Objectives 2 and 3
RQ5. How do optometrists' diagnostic decisions and trust in AI-CDSS change when exposed to ambiguous or incorrect AI outputs, and what is the impact of different presentation formats such as segmentation overlays?	Objectives 4 and 5
RQ6. How should outputs from an AI-CDSS be displayed to ensure they are clinically useful for optometrists?	Objectives 5 and 6
RQ7. At what point in the optometric consultation should an AI-CDSS for OCT interpretation be introduced to align with clinical workflows?	Objective 6

Table 22: Mapping of research questions to the study objective(s).

6.2 Methodology

The Ethics application for this study was approved by the UCL interaction centre, department ethics committee in October 2022. UCL Research Ethics Committee Approval ID Number: UCLIC_2022_008_Blandford _Carmichael_Costanza.

6.2.1 Participants and Recruitment

Purposive sampling was applied to recruit participants who are representative of the relevant professional group: optometrists. Participants also met the following inclusion criteria to participate:

- Able to communicate in English, understand the study, and give informed consent.
- Must be qualified with an active general optical council (GOC) registration. No minimum years' experience will be required.
- Working mainly in primary care practice. i.e., this must be where they spend most of their working time.
- Working in a primary care practice that offers OCT retinal imaging to patients. This can be with or without other advanced retinal imaging such as widefield.

Pre-registration optometrists or optometrists working mainly (defined as more than 50% of their working time) in the HES were not eligible to take part in the study. Participants were recruited to include optometrists working in both multiple and independent practices, and to cover a large range of years' experience. Twenty optometrists working in primary care were recruited.

Initial recruitment took place via open social media groups for optometrists. As this method of recruitment mainly attracted participants with less than 10 years since qualification, snowball sampling was also used to reach participants who have been qualified for longer, in order to diversify the sample of participants. Participants were offered a £50 Amazon voucher as reimbursement for an hour of their time.

A total of twenty optometrists working in primary care were recruited. Recruitment continued until data saturation was achieved, defined as the point at which additional interviews no longer generated new themes or substantive insights relevant to the research aims. Saturation was determined during ongoing data collection and initial familiarisation with the data, after which recruitment ceased.

6.3 Procedure

6.3.1 Semi-structured Interviews

Data collection started in December 2022 and was completed by the end of February 2023. The interviews were conducted online via Microsoft Teams and focused on optometrists working in primary care practices. All interviews were semi-structured (See Appendix 3.3 for the Interview Topic Guide), to address the study aims whilst creating flexibility to be able to follow up on new insights as they emerge. All interviews were audio-recorded and transcribed verbatim. Screen recordings were used to identify the parts of OCT scans that optometrists were referring to when using ‘think-aloud’ to assess clinical cases and AI outputs.

To explore optometrists' information seeking when encountering clinical cases that they regard as 'challenging', the 'critical decision method' (CDM) was used when carrying out this part of the interview. This method focuses on participants' retrospective recalling and analysis of 'critical incidents' they have experienced and may be used to help participants elicit details of memorable past patient encounters (212). This approach is designed to allow interviewers and interviewees to work together and reconstruct their thought processes and actions when dealing with a problematic situation where they may have needed to make a difficult decision based on limited knowledge (213). An advantage of this method is that it allows recall bias to be minimised in order to help interviewees to recall incidents as accurately as possible (212). The method of CDM was also complemented with the participant recalling the most recent case for which they had to seek information. Although this was likely to be less 'critical' it will still likely be memorable to participants.

In addition to the CDM, Leckie et al's 'Model of the Information-Seeking of Professionals' (214) was used as a theoretical approach when both gathering and analysing interview data. This model focusses on information-seeking by professionals at work and assumes that the daily tasks undertaken by professionals in practice prompt specific information needs, thus initiating the process of information seeking. The model comprises six components: 1. work roles, 2. associated tasks, 3. characteristics of information needs, 4. awareness, 5. sources, and 6. outcomes. The latter three components interact to influence information seeking.

In all interviews, a semi-structured topic guide was used which was based on questions related to the research topic (Appendix 3.3). The interview procedure followed 6 stages:

Stage 1. Introducing the Research
Introduction of the research topic and confirmation that the participants are aware of its purpose. Reaffirming confidentiality and right to withdrawal at any point. Permission to begin audio-recording the interview.

Stage 2. Background Information
Gaining information about the participant in relation to their employment, years of experience and type(s) of optometry practice(s) worked in.

Stage 3. Interview around experience of OCT interpretation and use in clinical workflows
Confirming that the participant regularly works in a practice with OCT imaging available. At this stage, questions were straightforward and focused on where OCT imaging fits into workflows i.e. how often they are performed and how this is decided, who captures the images and how often results are discussed with patients.

Questions were also asked about what training optometrists have received, both previous and ongoing, and whether they felt this training was sufficient for interpreting the imaging results independently.

Stage 4. Interview around information seeking for memorable cases

Aiming to gain detailed information about the topic whilst employing CDM to encourage participants to draw on their memorable experiences. Leckie's model of information seeking (214) components was used to inform the questions asked during this stage. Questions were asked based on memorable clinical cases for all ocular conditions, before specifically focussing on memorable findings from OCT imaging.

Stage 5. Assessment of ambiguous clinical cases

Participants were presented with three ambiguous clinical cases that include retinal OCT imaging (Figure 7) and were given control of the researcher's screen to scroll through OCT scans. They were asked to assess each case, provide a tentative diagnosis and management plan, and 'think-aloud' when doing so. Participants were questioned on whether they could manage this patient independently and if there would be additional information/advice they would seek and where.

Stage 6. Interview around potential for AI use in primary care (with demonstrations)

The aim of this stage was to gain detailed information around participants' thoughts about the potential future use of AI in primary care optometry as a CDSS. Demonstrations (detailed below, Figure 15) of an AI system for OCT imaging interpretation were shown for the same three ambiguous clinical cases that were previously demonstrated, in the same order. Questions were asked around specific features of the system. This stage focused on three components of Leckie et al's model: 4. Awareness - through demonstrating an AI system that could be used as support. 2. Associated tasks - by offering a theoretical diagnostic task that this tool could provide support for through examples of suspect retinal disease. 3. characteristics of information needs - through aiming questions towards which information, in the participant's opinion, demonstrated by the AI fits the information needs for these diagnostic and management tasks.

Stage 6. Close the interview

This stage involved ending the interview stages and asking the participant if they wished to express any more thoughts or offer any more relevant information. The participant was thanked for their participation.

6.3.2 Think-alouds

During stage 5 of the interviews, participants were shown 3 challenging clinical cases of suspected retinal disease, consisting of dry AMD, central serous chorioretinopathy (CSR/CSCR) and a partial thickness macular hole (PTMH). The information shown to the participant was a macular volume OCT scan, fundus image and basic clinical information (age, sex and visual acuity, symptoms) (Figure 14). The participant was asked to 'think-aloud' as they assessed the case before suggesting a possible diagnosis and management decision. They were asked questions around whether they feel like they could manage this patient without seeking further advice and, if they were to seek advice/information, what advice they would seek and where.

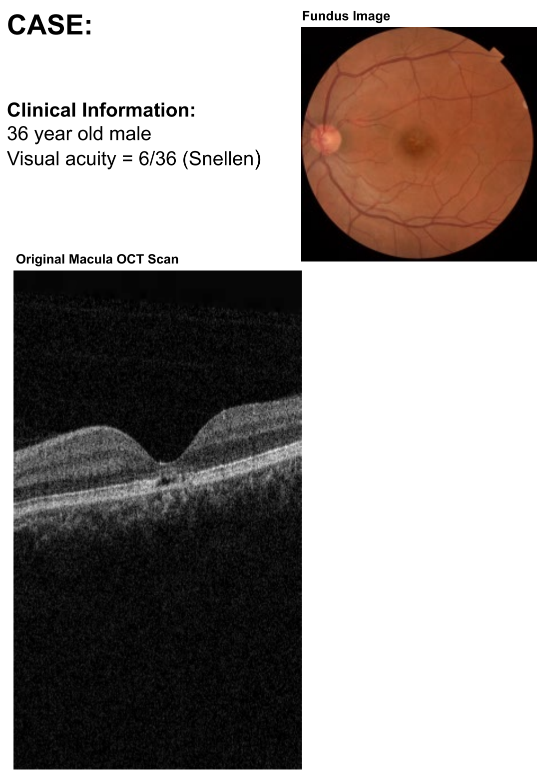

Figure 14: Information demonstrated to participants during stage 5 of the interview study. A challengng clinical case whereby basic clinical information, a fundus image and OCT volume scan are presented to participants.

6.3.3 Demonstrations

After the participant assessed each clinical case, they were shown additional information from outputs produced by the Moorfields-Google-DeepMind AI model (157).

Participants were asked a series of questions around the outputs from the AI diagnostic support system. The questions around the segmentations focused on their usefulness, clarity and presentation design. The questions around the diagnostic algorithm focused on usefulness and level of information provided. Participants were asked to suggest any alternative methods of presenting the outputs.

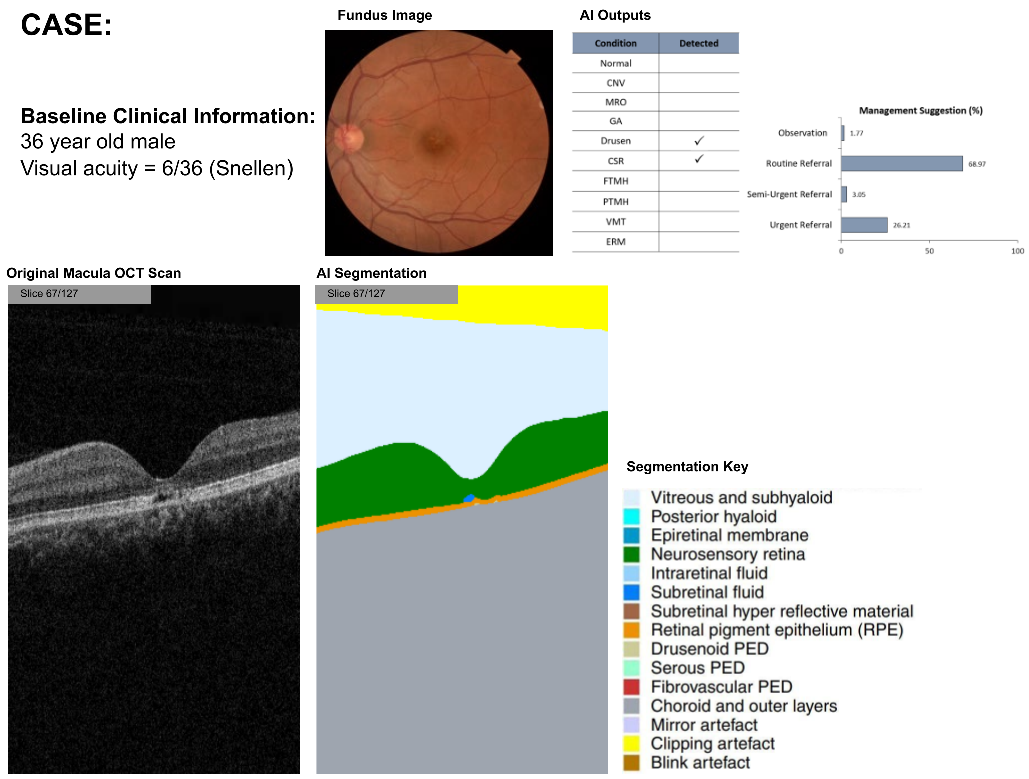

Figure 15: Information demonstrated to participants during stage 5 of the interview study. An clinical case was used to demonstrate how AI information could be available as additional information to aid optometrists in making diagnostic decisions. 'AI Segmentaion' displays segmention overlays produced by an AI system which highlights colour-coded anatomical and pathological OCT features. 'AI Outputs' displays the AI's diagnostic and referral suggestions using multi-class probabilities. These probabilities are displayed as a percentage out of 100%

6.4 Data Analysis

A combination of deductive and inductive thematic analysis was used to analyse the data. NVivo qualitative analysis software was used to manage transcripts, support systematic coding, and enable iterative refinement of codes and themes across the dataset. Preliminary data analysis began early on, through listening to audio recordings and reading transcripts. At this stage, the analysis was open, to explore any themes that were identified.

6.4.1 Deductive analysis

For the data around optometrists' information seeking behaviours, analysis was carried out deductively whereby the generated codes were informed by the research question. For this analysis codes were generated to fit within the 6 components of Leckie's model. 1. work roles, 2. associated tasks, 3. characteristics of information needs, 4. awareness, 5. sources, and 6. outcomes. Findings were linked to these components and the factors within these components, described by Leckie and colleagues (214).

6.4.2 Inductive analysis

For the data relating to optometrists' views on AI support and the AI systems demonstrated, an inductive approach was used. The data were analysed using open coding with iterative analysis. Inductive methods were used for this data as there was no current published theory in relation to optometrists' interactions with new AI CDSS systems at the time of writing.

The findings from the deductive and inductive analyses are covered in detail in Chapters 7-9. A discussion of these findings can be found in Chapter 10.

Chapter 7: OCT in Practice

The way in which OCT is integrated into primary care optometric practice varies significantly based on individual, structural, and contextual factors. This chapter explores how optometrists incorporate OCT into their clinical workflows, focusing on its role in the eye examination, the influence of practitioner experience and background, and the impact of case complexity on decision-making.

The chapter is structured into three key sections. First, 'Participant Profiles', provides insight into the diverse backgrounds, experience, and clinical environments of the optometrists participating in this study. This section contextualises their perspectives on OCT use, acknowledging how factors such as years since qualification and exposure to the HES shape their confidence in interpreting OCT findings. Understanding these variations helps illustrate why OCT is perceived and utilised differently between practitioners. The second section, 'OCT and the Eye Examination' examines when and how OCT is introduced within the consultation process as well as the perceived benefits of having OCT available in primary care. This section covers whether optometrists review OCT findings before or after conducting their other clinical assessments and how these different approaches influence the eye examination. The final section, 'Management Complexity', covers how OCT findings may influence patient management decisions, particularly in cases where imaging highlights ambiguous or borderline pathology. This section explores how optometrists navigate uncertainty and determine the most appropriate patient management. It also considers how external pressures, such as varied referral pathways, can influence decision-making.

By examining these themes, this chapter provides a comprehensive look at how optometrists engage with OCT in primary care, illustrating both the benefits and challenges of integrating advanced ocular imaging into clinical practice.

7.1 Participant Profiles

The interview findings highlighted how optometrists' approaches to OCT are strongly influenced by their years since qualification. Participants who had qualified more recently often demonstrated a greater familiarity and comfort with OCT (even when unsure about their interpretation of results) whereas more experienced optometrists varied in their adoption, with some expressing hesitancy or using OCT more selectively.

To explore these differences, participants were broadly categorised into four groups based on their years since qualification and their relationship with OCT. These profiles illustrate how professional experience influences OCT adoption, decision-making, confidence, and patterns of use within practice. The following categorisations provide insight into these distinctions. The first two represent optometrists with up to 7 years of experience:

Newly qualified optometrists (Type 1): qualified for less than 2 years and view OCT as an integral part of their training and practice, showing enthusiasm and openness to learning. Comfortable getting things wrong.

OCT-integrated optometrists (Type 2): 4-7 years of experience and gained both formal training at university and experience with OCT since qualifying. They have therefore integrated OCT into their practice and have become more comfortable with the technology through practical use.

In contrast, those qualified for over nine years did not learn about OCT imaging at university or during their early career; they were therefore exposed to OCT imaging later in their careers and had to adapt their approach to the eye examination. Within the research participants, there is a clear divide within this level of experience, into two groups:

Experienced and hesitant (Type 3): Apprehensive, viewing OCT as complex and non-essential. They are worried about interpreting OCT imaging findings incorrectly.

Experienced and early adopters (Type 4): Embraced OCT technology, seeing it as a valuable tool for enhancing diagnostic accuracy.

In this section, I discuss these profiles in more detail, as well as align the latter two types with the broader framework of Rogers' Diffusion of Innovations Theory, illustrating how familiarity, perceived advantage, and professional context can drive or inhibit the adoption of new technologies in clinical practice.

7.1.1 Type 1 - Newly Qualified Optometrists.

This group comprises four of the 20 interviewed optometrists: **Participants 3, 4, 6 and 16**. These optometrists are relatively recent graduates who received foundational OCT training during their university studies, with some also gaining practical experience using OCT on patients while still in training. Despite their limited years of practice, they demonstrate a notable comfort with OCT interpretation, approaching it with curiosity and enthusiasm. Unlike more experienced practitioners who may feel pressured to master OCT immediately, this group embraces the ongoing learning process as a natural part of their professional development. As **Participant 16** explained, *"There's always more that you can learn with OCT, I think. I feel like I am always learning, which is good"*. Similarly, **Participant 4** acknowledged that while confident in some aspects of OCT use, they are still exploring its full capabilities: *"I'm not very confident with exploring the other scans and what they can do or interpreting those as such. I'm still learning about those at the moment"*.

A key characteristic of this group is their reliance on discussions with colleagues to support their learning. When faced with uncertainty in OCT interpretation, they frequently seek guidance from more experienced practitioners, often viewing these exchanges as extensions of their pre-registration training. **Participant 16**, for example, described how they continue to turn to a former pre-registration supervisor for advice, maintaining a mentor-mentee dynamic that provides reassurance and guidance: *"My manager was also my pre-reg supervisor, so I ask her a lot because she knows a lot. So, I'd go to her as first port of call"*. Similarly, **Participant 6** highlighted the value of having experienced colleagues available for second opinions: *"Normally when I'm working, there'll be at least one other person, normally two. So, if I have looked at the scan before calling a patient in and I'm unsure, I can normally get them to look at the scan before I have actually called the patient in to get a second opinion. So definitely if it's a colleague that's more experienced than myself, they'll know things that I don't, or it can be just a reassurance. I can go in and say, 'I think it's this,' but sometimes you just want someone to confirm that they're thinking along the same lines as you"*.

Beyond seeking reassurance, this group also actively engages in peer learning, viewing discussions about OCT as opportunities for mutual knowledge-sharing rather than simply a means to confirm their own interpretations. As **Participant 4** noted, *"I often do double check sort of my finding, even if I'm almost a hundred percent certain what it is because I think we all like learning from each other anyway, and if we find anything interesting, it's quite beneficial"*.

The enthusiasm of this group toward OCT extends beyond clinical necessity, with many expressing a genuine interest in the technology. Some participants even described OCT as "cool," demonstrating an eagerness to explore complex or unusual cases. **Participant 3**, for example, shared how they and their colleagues often highlight intriguing OCT findings to one another: *"Yeah, and if any of us have something interesting, we'll normally like say, 'Oh, check the OCT for this because it's really cool.'*

This enthusiasm is further reflected in how these optometrists engage with external learning platforms. Some actively participate in OCT discussion forums, using them as resources to expand their knowledge. **Participant 6**, for example, described how they follow OCT case discussions within an online group: *"I'm part of the OCT groups on there, so I've never actually posted anything, but I will often have a look and read through interesting OCT cases that other people are posting in there"*. By engaging with both colleagues and external resources, this group demonstrates a commitment to developing their OCT expertise, approaching its use in clinical practice as both a learning opportunity and a means of professional growth.

7.1.2 Type 2 - OCT Integrated Optometrists

This group includes six of the interviewed optometrists: **Participants 5, 8, 10, 11, 14, and 15.** Their exposure to OCT technology before entering their pre-registration year varied, largely depending on the level of training provided by their university. While all participants had at least a basic awareness of OCT imaging and its clinical applications, the depth of their understanding differed depending on their institution's curriculum.

Participant 8 reflected on their limited OCT training at university, noting that while they were introduced to the technology, it was not covered in detail: *"We did have OCT in our university clinics. We dabbled into it, but we never did any certain lectures. We didn't do much. We knew OCT was a thing, but it wasn't like taught or we wouldn't have looked at any scans. We would've had maybe images of pathology* *with maybe an OCT scan or so with it, but nothing in detail, we wouldn't be able to tell what part of the scan is what [..] to what I can recall"*.

Although the extent of initial OCT exposure was varied in this group of participants, this early introduction meant that by the time they entered their pre-registration year, they were already familiar with the potential benefits of OCT in optometric practice. Like the newly qualified group, these optometrists find OCT cases engaging and continue to develop their expertise through clinical experience. **Participant 15** described how they actively seek out opportunities to refine their skills by reviewing challenging cases: *"I quite like seeing more unusual things. Like if someone is familiar with OCT, if they upload it up to the group, it's nice for me to test myself or challenge myself. So, I quite like learning, you learn a lot from seeing things like that"*.

During the early stages of their professional careers, either during pre-registration or soon after, all participants had the opportunity to work directly with OCT technology. This early exposure allowed them to integrate OCT into their clinical routines from the outset, providing them with a strong foundation in its application. Unlike newly qualified optometrists who are still building their confidence in OCT interpretation, these practitioners have had several years to develop their skills. Their OCT knowledge has improved alongside their broader clinical experience, enabling them to become increasingly confident in independent OCT interpretation. As **Participant 15** explained: *"I've grown up with OCT so I've [..] never not worked with one. So, you just begin to learn what to expect. Yeah. So, sort of organic, I think"*. **Participant 5** also highlighted how regular exposure to OCT has helped build confidence over time: *"I think that to begin with I wasn't confident with [OCT interpretation], but yes, with using it so often since I started, I think now I am, through the few years of experience"*.

As these optometrists have used OCT from the beginning of their careers, their proficiency with the technology has evolved alongside their broader clinical skills. This parallel development means that their confidence in OCT interpretation is closely aligned with their overall diagnostic abilities, allowing them to easily integrate the technology into their clinical practice.

7.1.3 Type 3 - Experienced (9+ years) and hesitant

This group consists of four interviewed optometrists: **Participants 1, 2, 7 and 17**. Unlike more recently qualified practitioners, these participants did not receive formal OCT training during their university education and practiced for several years without exposure to the technology. At the time of their qualification, OCT was primarily used in specialist settings rather than in routine optometric practice. As a result, when OCT was eventually introduced into their workplaces, they had limited familiarity with the equipment and its interpretation. **Participant 7** described how the introduction of OCT after graduation left them feeling unprepared: *"I always felt OCT sort of shot up a few years perhaps after I left university. So, we didn't really get any formal training from university, which was quite a shame. Um, so the first few times I was exposed to it, I was, you know, I had absolutely no idea what it meant"*.

Due to this lack of training, some participants expressed a negative attitude towards the use of OCT, largely because it felt like an additional burden rather than an enhancement to their diagnostic process. Their discomfort stemmed from being introduced to OCT later in their careers, making it harder to integrate into their established routines. When asked if they used OCT in primary care, **Participant 2** responded with *"Yes, unfortunately"*, reflecting a reluctance to engage with the technology. Similarly, **Participant 1** was critical of the way OCT had been introduced into practice without structured training: *"I find it shocking how people are just given a machine and they're like, good luck, and it's entirely on you, and there's no check and balance to see"*. This sense of being left to figure things out independently contributed to the group's frustration and hesitancy in using OCT confidently.

For some participants, this discomfort led to actively avoiding practices that used OCT, particularly those who had the flexibility to choose their work environments. Instead of learning to use OCT, they sought out workplaces where they could continue relying on traditional diagnostic methods. **Participant 2** openly admitted to resisting OCT adoption for as long as possible: *"I tried to resist OCT for quite a number of years and I started locuming in places where they didn't have OCTs, and then eventually got to a stage where, um, it has become quite difficult to do so"*.

Even among those who do use OCT in practice, there was a common lack of confidence in interpreting scans. Participants were open about their uncertainty, acknowledging gaps in their knowledge despite their extensive clinical experience. **Participant 7** described their struggles with OCT interpretation: *"I wouldn't say I'm wholeheartedly confident with OCT. There's a lot that still throws me off"*. Similarly, **Participant 1** admitted that OCT interpretation remained a source of stress: *"I feel more competent with it [..] and when I say competent, I just mean I'm able to sleep after I've done an OCT"*.

Due to their lack of confidence, these optometrists tended to adopt a cautious approach to patient management, particularly when uncertain about an OCT finding. **Participant 17** acknowledged that when faced with difficult cases, they often over-refer patients to the HES to avoid any potential misdiagnosis and to "protect their registration." This highlights a contrast between this group and less experienced optometrists, who are typically more comfortable with learning on the job and view mistakes as part of their professional development. In contrast, these more experienced optometrists expressed greater discomfort with making mistakes.

7.1.4 Type 4 - Experienced (9+ years) and early adopters

This group consists of six interviewed optometrists: **Participants 9, 12, 13, 18, 19 and 20**. In contrast to others with similar levels of experience who expressed hesitancy toward OCT, this group was positive about the technology and open to integrating it into their clinical practice to embrace OCT as a valuable diagnostic tool.

Some of these participants worked in or owned practices that were early adopters of OCT, integrating the technology before it became widespread in primary care. **Participant 12** noted that their practice introduced OCT in 2013, while **Participant 9** actively chose to implement it early in his practice: *"In terms of OCT, we tend to be quite early adopters of technology. So, we've had an OCT in practice for what, I'm trying to think now, probably about eight years, maybe, maybe eight, 10 years."*

In addition to early adoption in primary care, some participants had gained valuable OCT experience in hospital settings, which further strengthened their confidence in using the technology. **Participant 9** and **Participant 13** had both worked in the HES, where they were regularly exposed to OCT for diagnosing and managing complex cases. This experience likely provided them with a deeper understanding of OCT's clinical applications, reinforcing its role in their own practices.

All participants in this group recognised the significant benefits of incorporating OCT into primary care, viewing it as a useful tool patient management. **Participant 18** also highlighted its value in patient education, particularly in explaining age-related macular degeneration and encouraging proactive self-monitoring: *“For patient education, particularly in terms of sort of dry AMD, it's useful to show those changes and then talk about the modifiable risk factors and Amsler monitoring.”*

Similarly, **Participant 19** reflected on how OCT had transformed clinical decision-making by eliminating diagnostic uncertainty in cases of unexplained vision loss: *“Obviously, without the OCT before, if you've got an unexplained drop in vision, you're always guessing. But with OCT technology, you've got the advantage of that. So, if it's a macular problem, you're not going to spend ages refracting them. If you know it's a wet AMD patient, you're just going to end up doing fundoscopy and referring them on. So, it does, it does help massively now, uh, there is a big advantage of it.”*

Having integrated OCT into their routine workflows, all Type 4 participants expressed confidence in independently interpreting scans. Unlike less experienced practitioners, who often seek second opinions, this group demonstrated a strong sense of autonomy in their use of OCT. **Participant 20** explained how familiarity with the technology over time had contributed to this confidence: *“I think most of the time the things that you see, you've probably seen maybe a few times, and you just end up learning them. So yeah, I think most of the time I do tend to, you know, interpret them by myself.”*

This group’s willingness to actively engage with OCT, seek additional training, and integrate it into their practice sets them apart from others with similar years of experience who resisted its adoption. Their proactive approach to learning and confidence in independent interpretation highlight the benefits of embracing new technology in optometric practice.

7.1.5 Links to Rogers' Diffusion of Innovations Theory

As Type 1 and Type 2 optometrists were exposed to OCT early in their training and practice, the technology integrated into their workflows easily. In contrast, Type 3 and Type 4 participants qualified before the widespread adoption of OCT and had to adapt their clinical practice to incorporate OCT. Their varying responses to this transition align with Rogers' Diffusion of Innovations Theory (215), which categorises individuals based on how quickly they adopt new technologies. The following section provides an overview of the theory and a deductive analysis of Type 3 and Type 4 participants to explore the factors influencing their experiences with OCT implementation.

Rogers' Diffusion of Innovations Theory (215) outlines five categories of adopters based on the speed at which they integrate new technologies or practices: innovators, early adopters, early majority, late majority, and laggards. Several key factors influence the rate of adoption:

1. **Relative Advantage** -The perceived benefit of the innovation over existing methods.
2. **Compatibility** - How well the innovation aligns with the adopter's values, needs, and previous experiences.
3. **Complexity** - The difficulty of understanding and using the innovation.
4. **Trialability** - The extent to which the innovation can be tested before full adoption.
5. **Observability** - The visibility of the innovation's benefits to others.

In the interview study, Type 3 users (those qualified for over nine years but hesitant or reluctant to use OCT) closely align with Rogers' late majority and laggards. Their slow adoption appears to be influenced by the *complexity* of the technology and a lack of *compatibility* with their established clinical routines. **Participant 7** described their early experiences with OCT as overwhelming due to a lack of foundational knowledge: *"The first few times I was exposed to it, I was, you know, I had absolutely no idea what it meant."* **Participant 2** similarly expressed ongoing uncertainty about OCT interpretation: *"You can look at all these scenarios when you look at an OCT, it never comes up the same. And yeah, I just don't have the confidence in OCT."* For these optometrists, OCT is perceived as difficult to integrate into long-standing diagnostic methods, making its use feel disruptive rather than beneficial.

A key factor in adoption is *trialability,* as optometrists are less likely to integrate OCT without sufficient opportunities for guided, low-risk practice. When these opportunities are unavailable, practitioners may struggle to adopt the technology effectively. **Participant 17** described how missing the initial training phase in their practice left them at a disadvantage: *"OCT was installed while I was on maternity leave [..]. The engineer came and taught the floor staff how to take a photo, but I had no training on interpretation. I had no company training on interpretation or how to use the equipment. Obviously, because I was on maternity leave, I missed the initial training period."*

In contrast, Type 4 users, who also qualified over nine years ago but have actively embraced OCT, align more closely with Rogers' early adopters or early majority. Unlike Type 3 practitioners, they recognised the *relative advantages* of OCT early on, seeing it as a valuable tool for improving diagnostic accuracy and patient care.

Their adoption was facilitated by a willingness to explore new technologies and a high level of *compatibility* with their existing clinical needs, allowing them to incorporate OCT without disrupting workflow. *Observability* also played an important role, as these optometrists witnessed positive results from OCT use, such as improved diagnostic outcomes and greater patient satisfaction, reinforcing their decision to use the technology. For example, **Participant 9 and Participant 13** had prior experience working in the HES, where OCT was routinely used. This early exposure allowed them to observe the benefits of OCT, strengthening their confidence in its diagnostic value. Their HES experience also contributed to the *trialability* of OCT, as they were able to learn from more experienced clinicians in a low-risk environment before integrating it into their own practice.

Overall, Type 3 and Type 4 optometrists demonstrate two contrasting approaches to OCT adoption. While Type 3 practitioners struggle with integrating the technology due to lack of training/exposure, compatibility issues, and low confidence, Type 4 practitioners actively sought learning opportunities, embraced OCT's advantages, and successfully incorporated it into their workflows. These differences highlight the importance of structured training, exposure and guided implementation in facilitating the adoption of new technologies in optometric practice.

7.2 OCT and the Eye Examination

The way in which OCT imaging fits into the eye examination can vary based on optometry practice set up. The interviewed participants working in smaller, independent run practices described how OCT is either offered by the optometrist at the beginning of the appointment or during the examination. For some optometrists, this is only offered if they feel the patient is higher risk e.g., older age. In independent practices, optometrists tend to perform the scanning with the patient themselves. Participants working in multiple practice (i.e., large UK optical chains such as Specsavers or Vision Express), described how in general, OCT imaging is offered to the patient at the time of booking or checking in for their appointment. In this context, it is offered by a member of non-clinical staff and if the patient accepts with the additional fee, the OCT imaging is often carried out during the pre-screening part of the appointment also by a non-clinical member of staff. If a patient declines the imaging, the optometrist has the option to request it after seeing the patient, if they feel there is a clinical need.

Most optometrists reported that they would always discuss results of the OCT imaging with patients, regardless of whether the scan was ‘normal’ or not, and this was because OCT imaging usually required an additional fee from patients. For example, **Participant 7** stated: *“I mean at the end of the day they have paid an additional fee, so you have to show them what essentially they've paid for, but also, I always find they're a little bit more curious than in the bog standard digital retinal photography nowadays”*

7.2.1 Perceived Benefits of OCT imaging

Through practitioners' experiences and reflections during the interviews, several key perceived benefits of having OCT imaging in practice were identified; Early Detection, Comprehensive Patient Records and Continuity of Care, Increased Diagnostic Confidence and Efficiency. The following section explores these advantages, illustrating the ways in which OCT supports both optometrists and their patients.

Early Detection

OCT’s ability to detect subtle, early-stage changes in the retina that may be difficult to identify through standard examination methods makes it an invaluable tool for the early diagnosis of eye diseases. Practitioners appreciated this advantage of having OCT and highlighted that it is especially effective in identifying structural changes in the deeper layers of the retina, such as fluid accumulation or retinal thinning, which might not be apparent during ophthalmoscopy or with traditional fundus photography. The ability to detect these abnormalities at a pre-symptomatic stage could have a significant impact on disease management and outcomes. **Participant 16** reflected on a case where OCT revealed fluid build-up that was not visible on standard fundus photography, reinforcing its clinical importance: *"My colleague said that she wouldn't have spotted [the abnormality] either because the photos, the flat photos looked fine, and the OCT showed up this level of fluid. So that one kind of made me think, yeah, OCT is really important, I need to do this on more people".* This highlights the critical role OCT plays in uncovering otherwise undetectable pathology.

Comprehensive Patient Records and Continuity of Care

The ability to maintain comprehensive patient records and ensure continuity of care was identified as a significant benefit of incorporating OCT imaging into primary care. OCT facilitates the collection of detailed, long-term records of a patient's retinal health, allowing clinicians to track subtle changes over time. This longitudinal record of retinal structure is particularly valuable when assessing whether an observed retinal feature is part of a stable, long-standing condition or an emerging pathological change requiring intervention. As **Participant 11** highlighted, routine OCT imaging provides an important reference point for follow up assessments: *"Everybody gets that OCT as standard because, you know, they are really useful for long-term monitoring, even if they're normal, because next time something's not normal, we don't know if that is normal or not, if that makes sense"*. This reinforces the role of OCT in proactive patient management, ensuring that deviations from baseline retinal health can be accurately identified and acted upon. **Participant 3** also reflected on the value of having accumulated years of OCT records: *"We've had our OCT since, um, twenty twelve or twenty thirteen. Um, so it's very useful to have historical records to compare to when you're managing patients"*. This longitudinal perspective is particularly beneficial when assessing progressive conditions such as age-related macular degeneration or glaucoma, where identifying subtle changes over time can be critical to early intervention.

Increased Diagnostic Confidence

For some clinicians, OCT enhances diagnostic confidence by providing detailed anatomical insights that support clinical decision-making. This increased diagnostic certainty is particularly valuable in macular cases, where distinguishing between common, benign changes and more serious pathology is essential. Several participants highlighted the role of OCT in assessing suspected wet age-related macular degeneration (AMD), a condition where early and accurate diagnosis is critical to initiating timely treatment. OCT allows practitioners to confirm or rule out the presence of fluid or other pathological features. **Participant 14** described how access to OCT imaging significantly increased their confidence in both diagnosis and patient management: *"[OCT] makes me more confident about my diagnosis and management. Yeah, definitely way more confident. Especially if someone has on their previous records like drusen or RPE changes, and if they've had a drop in vision. If I didn't have the OCT, I think I would be more likely to refer for suspect wet AMD if I wasn't sure*". This insight highlights how OCT can provide clarity in cases where fundus examination alone may leave room for uncertainty. By offering objective, high-resolution imaging, OCT helps clinicians make more informed decisions, ensuring that referrals are reserved for cases where intervention is truly warranted.

Efficiency

Efficiency was identified as a benefit of OCT imaging, particularly in its ability to streamline the diagnostic process and reduce reliance on additional, time-consuming tests such as dilated fundus examinations. By providing cross-sectional images of the retina within seconds, OCT enables clinicians to gather comprehensive diagnostic information quickly, which ultimately enhances workflow efficiency. This not only saves time for practitioners but also reduces patient contact time during appointments. This reduction in patient contact time became especially valuable during the COVID-19 pandemic, when minimising face-to-face interactions was a priority. **Participant 3** reflected on how the use of OCT increased during this period to avoid the delays associated with pupil dilation: *"During COVID, to minimise test times, the OCT got used more because it was far easier to work out what was going wrong from a quick scan. You didn't have to wait for them to dilate, so you know, you saved twenty minutes of patient contact".* This illustrates how OCT not only enhanced diagnostic efficiency but also played a role in adapting workflows during pandemic-related constraints.

7.2.2 OCT as an Integral Piece of Information

Given the highlighted benefits of OCT imaging, some optometrists consider it an essential part of the eye examination rather than an optional tool. These participants recognised its value in detecting subtle structural changes in the retina that may not be visible through traditional examination techniques alone. As a result, OCT is not merely used as a confirmatory test but as an integral component of clinical assessment, enhancing optometrists' ability to make earlier and more accurate diagnoses, particularly for conditions such as macular degeneration. This shift in approach is reflected in the fact that most participants (n=14) stated that if OCT imaging is available or if they are performing the scan themselves, they will review the images at the beginning of the appointment.

Several reasons were cited for this preference. One key advantage is that viewing OCT data beforehand allows for a more targeted clinical examination. With an initial understanding of retinal findings, optometrists can tailor their assessments by focusing on specific concerns, performing additional relevant tests, and asking further questions about patient history. **Participant 13** described how this structured approach improves efficiency: *"I always [check the OCT scan] before. It will guide and tailor the sight test. So, it often makes it more efficient"*.

This proactive use of OCT also supports decision-making in patient management, as practitioners can immediately gauge the level of urgency required. **Participant 14** provided an example of how initial OCT findings influence clinical decisions: *"I mean if I saw fluid at the macula or something, I would automatically convert it to a MECS if it had come in as a routine one [..] or if it was just some little drusen or something, I would do an Amsler chart, which I might not have done otherwise"*. By identifying abnormalities early in the consultation, optometrists can make real-time adjustments to their examination and management plans, in this case to change the appointment from a routine eye examination to a more targeted minor eye case service (MECS) appointment.

Another important benefit of reviewing OCT scans at the start of the appointment is its impact on patient history-taking. With prior knowledge of the scan results, optometrists can ask more specific and clinically relevant questions, tailoring the history-taking process to align with potential diagnoses. **Participant 14** explained how OCT findings shape the direction of questioning: *“Say there are some clinical signs, for example, if there’s like fluid at the macula, I might ask questions more specific to that. Um, so I might say ‘have you noticed any distortion?’ whereas typically I wouldn’t ask that in a normal history and symptoms. Or if someone had noticed a reduction in vision, I might be a bit more like, asking about the timeline and how quickly it happened”*.

Additionally, reviewing OCT results early in the appointment can help set patient expectations and guide communication during the examination. By having an informed perspective before beginning the physical assessment, optometrists can prioritise discussing clinically significant findings rather than spending excessive time on less critical aspects of the consultation. **Participant 15** emphasised the importance of directing appointment time toward the most urgent clinical issues: *“I know there's a more pressing thing to get sorted [..] I’m not going to spend five minutes refining someone's vision in an eye that's got wet AMD. I often feel that you're better off prioritising having a conversation with the patient about the clinically relevant findings”*.

By integrating OCT imaging at the start of the appointment, optometrists can enhance the efficiency and relevance of their examinations, leading to a more targeted approach.

7.2.3 OCT as an Additional Piece of Information

While some optometrists consider OCT an integral part of the eye examination, others use it as a supplementary tool. This distinction is evident in the approach taken by participants who choose to view OCT images at the end of the consultation rather than at the beginning. Six participants stated that they review OCT findings after completing the eye examination, with one participant noting that despite choosing to take the scan at the start, they prefer to analyse it only at the end.

For some optometrists, delaying the review of OCT findings, in their view, ensures that their clinical examination remains unbiased. By conducting the physical assessment without prior knowledge of the OCT results, they feel that the risk of overinterpreting subtle OCT features that may not be clinically significant is reduced. This method allows practitioners to make an initial diagnostic judgement based solely on ‘traditional’ techniques, before using OCT as a secondary tool to validate or refine their conclusions. **Participant 2** explained their reasoning behind this approach: *“The reason why I [view the OCT at the end of the eye examination] is I'm very fussy about how good I am as a clinician. I'm confident in my clinical skills and I don’t like to rely on [the OCT findings]. So, it's always nice to do the clinical examination first and then back it up with what other things find, which is a bit backward, but it's just how I like to work”*. This perspective highlights the use of OCT to support rather than dictate clinical decision-making.

However, it was apparent that reviewing OCT findings after the examination is not without its perceived challenges. One point that was highlighted is contradictions between the clinical examination results and the interpretation of OCT findings. When an optometrist makes an initial judgement about a condition based on the physical exam, unexpected OCT results can introduce uncertainty and force a re-evaluation of their initial impression. **Participant 20** described an instance where their expectations based on the fundus examination did not align with their interpretation of the OCT findings: *“There was a patient who presented with some haemorrhages on the fundus. It was obvious on [slit lamp examination]. And when we did OCT, the haemorrhages were sandwiched very much on the surface of the retina between the vitreous jelly and the surface of the retina. But as you scroll across, it looked like a vein occlusion, but then it was nowhere near the macula [..] and it just threw me, because all the haemorrhages were far away from there [..] and it just completely threw me and I was like, is that oedema? I don’t understand how it could be oedema, but it must be oedema”*. This highlights how post-exam OCT review can sometimes challenge initial assumptions, requiring the clinician to reconsider their diagnostic reasoning.

These contradictions were also observed during the case demonstrations, where some clinicians initially assessed fundus images, and expressed their assumptions, before reviewing the corresponding OCT scans. In some instances, their preliminary diagnoses were overturned by the scan results, demonstrating how fundus examination alone may lead to incorrect assumptions. **Practitioner 1** reflected on a case where they initially suspected central serous retinopathy (CSR) based on the fundus image, only to realise that the OCT findings did not support this diagnosis: *“But I don’t know, I mean, without the OCT I thought there was going to be an* *element of CSR. Like, I thought that that sort of white ring [on the fundus image] was suggesting there was. But on the OCT, there's obviously not, um, not a CSR"*.

In summary, reviewing OCT before the examination provides a guided and targeted approach, enabling optometrists to tailor their assessment based on imaging results. Conversely, viewing OCT at the end of the appointment allows for an examination that is perceived as more unbiased, ensuring that clinical observations are made independently before being supported by the scan. However, this approach can introduce challenges when OCT findings contradict the initial examination, prompting clinicians to reassess their assumptions. Ultimately, the decision of when to review OCT imaging influences the optometrist's diagnostic process, patient management strategies, and overall confidence in clinical decision-making. Figure 16 illustrates the two different decision-making workflows depending on whether OCT is reviewed before or after the eye examination.

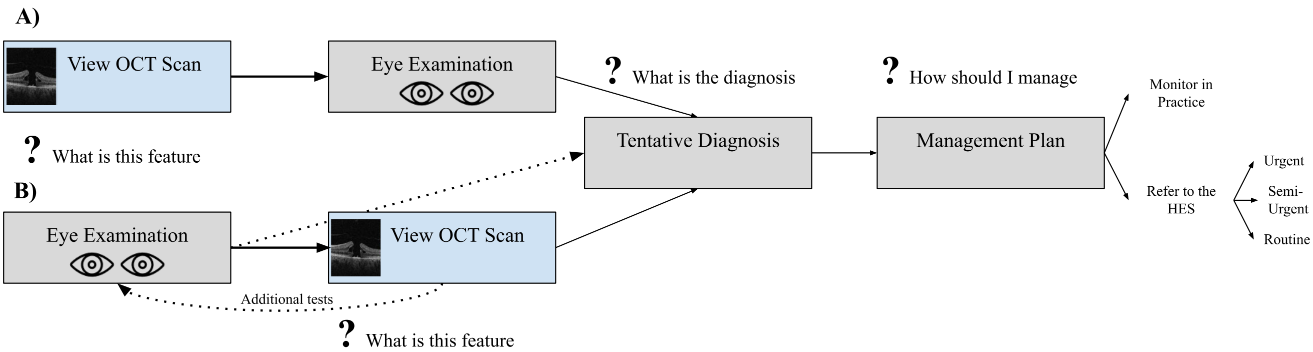

Figure 16: The two types of patient appointment pathways based on A) viewing the OCT scan before the main eye examination and B) viewing the OCT scan after the main eye examination. The three main points along the patient pathway where an optometrist may need to seek information to tentatively diagnose and/or manage a patient are also highlighted.

7.2.4 Links to Experience with OCT

The variation in how optometrists integrate OCT into the eye examination appears to be influenced by the number of years since qualification. A notable trend emerged, with four of the six optometrists who reviewed OCT results at the end of the eye examination having over 20 years of experience. Among these practitioners, two openly expressed a lack of confidence in using OCT in practice (**Participants 1 and 2**), citing limited familiarity with the technology. **Participant 2** even admitted to actively avoiding working in practices that used OCT until its adoption became unavoidable: *“I tried to resist OCT for quite a number of years, and I started locuming in places where they didn’t have OCTs, and then eventually got to a stage where, um, it has become quite difficult to do so”*.

Similarly, **Participant 1** reflected on how uncertainty surrounding OCT interpretation had initially impacted their confidence, leading to hesitancy in incorporating it into routine examinations: *“I definitely felt scared of it as a machine. Um, and looking back, I don’t think I did it in all the situations I should have because I was a bit scared of it”*. This account highlights how some experienced optometrists perceived OCT as an intimidating or complex tool, which may have influenced their preference for using it as a confirmatory rather than a primary diagnostic resource.

For the other two more experienced practitioners (Participants 9 and 12), the approach to OCT was shaped by different considerations. **Participant 12** preferred to analyse the scan in detail after the appointment had finished, as this provided them with more time for thorough evaluation without the pressure of an ongoing consultation. Meanwhile, **Participant 9**, as the owner of the practice, adopted a more flexible, patient-led approach, performing OCT only when deemed necessary based on findings from their clinical assessment. Their decision-making was guided by the needs of the patient and the specific requirements of the case, rather than a fixed protocol.

The findings suggest that clinical experience and confidence in OCT interpretation play a key role in shaping optometrists’ approaches to its integration within the eye examination. Practitioners with less exposure to OCT earlier in their careers appear more inclined to use it as a secondary tool rather than as an essential part of the diagnostic process. Conversely, those with greater familiarity with OCT or influence over practice protocols may adopt a more personalised and adaptable approach to its use in patient management.

7.3 Complexity of Management Decisions in Primary Care

Clinical decision-making in primary care is often perceived as a straightforward process, where identifying a tentative diagnosis naturally leads to a clear management plan. This perspective simplifies complex clinical scenarios, presenting them as linear pathways in which a diagnosis directly informs the next steps in patient care (Figure 17).

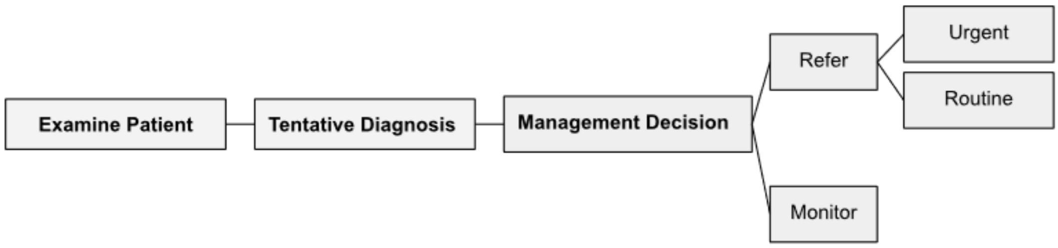

Figure 17: A simplified decsion making process for optometrists managing patients in primary care practice.

However, the interviews findings demonstrated that management decisions in practice are often more complex than simply choosing among three management options, based on a tentative diagnosis, particularly for cases that are more ambiguous. For instance, when opting to monitor a patient, the decision-making process extends beyond this initial choice and includes determining the most appropriate follow-up interval for the individual patient. In certain cases, more frequent follow-ups may be necessary to monitor for changes that could necessitate a referral to the HES. Figure 18 provides a summary of the factors that were identified from the interviews with optometrists. In the subsequent sections, these factors are explored in greater depth and analyse their impact on patient management decisions, organised under three main categories: Patient Factors, Optometrist Factors and External Factors.

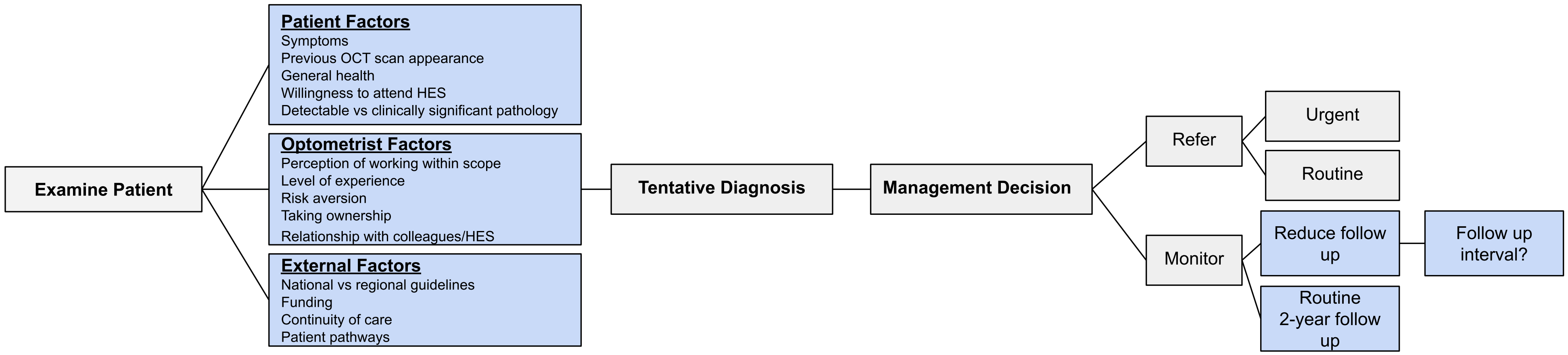

Figure 18: Decsion making process for optometrists managing patients in primary care practice, considering patient, optometrst and external factors that affect diagnostic and management decision

7.3.1 Patient Factors

When assessing OCT findings, optometrists must consider patient factors that can influence the interpretation and management of retinal findings. These factors can shape whether an OCT finding is deemed clinically significant, whether a patient requires referral to the HES, and the urgency of follow-up care. The interview findings highlighted two key themes for patient-related considerations that impact clinical decision-making: the availability of previous OCT scans for comparison and the patient's history, symptoms, and personal circumstances. By incorporating these elements, optometrists refine their diagnostic certainty and management decisions, ensuring that their approach is tailored to the individual.

Availability of Previous OCT Scans

The ability to compare current OCT findings with previous scans plays a crucial role in both tentative diagnosis and management decisions. Longitudinal OCT data enables optometrists to track changes over time, helping to determine whether an OCT abnormality is stable and longstanding, requiring no immediate intervention, or whether it is new or worsening, indicating a need for further investigation or referral. The importance of previous scans was emphasised by multiple participants. **Participant 12** explained how they routinely compare new findings with historical scans to determine whether a feature has changed, stating: *"What I would do is compare back to any previous scans or any previous ones to see if anything had changed or if that looked exactly the same as it did a few months ago or six months ago."* The availability of baseline OCT images allows optometrists to determine whether a feature has remained stable over time or if it is showing signs of progression. This was also echoed by **Participant 13**, who described how being able to access prior scans helped them refine referral decisions. They explained how in their practice, longitudinal follow-up was well-established, allowing them to confidently rule out referral in cases where a feature had remained unchanged: *"We're quite good for longitudinal follow-up [...] so I can look back and say, okay, so that was definitely there before. It's not changing in shape or size. Or if there's anything that's suddenly different, then that would tip me either way to refer or not. If this is new [...] or different to the previous visit, I would refer out or get an opinion from my local ophthalmologist."* When optometrists lack access to previous OCT scans, decision-making can become more conservative, often resulting in more referrals or shorter follow-up intervals to monitor potential changes.

History and Symptoms

Beyond structural abnormalities detected on OCT, optometrists place significant weight on the patient's symptoms, vision, and ocular/general health history when making management decisions. Symptoms provide crucial functional context, helping to distinguish between stable and progressive disease and determining the urgency of referral. Participants frequently highlighted the importance of understanding whether symptoms were recent, longstanding, or progressing. **Participant 14** illustrated how a sudden drop in visual acuity would influence their decision to refer, stating: *"It would depend on the previous ocular history. So, you'd want to know how long has the blurred vision been there for? Has it been a sudden drop or was it gradual? Was it since a significant event? Um, I think because it's... let's say he was 6/6 last time and now he's 6/36 a couple of years on, I would probably refer onwards because his vision has dropped significantly."* Similarly, **Participant 19** reinforced the significance of a decline in visual function, stating: *"If the vision was obviously 6/6 before and it's dropped to 6/36, then obviously I'll be more concerned."*

In addition to symptoms and history, optometrists consider social and lifestyle factors that may impact the likelihood of disease progression or a patient's ability to adhere to a management plan. **Participant 11** explained how they assess stress levels and occupation when suspecting central serous retinopathy, stating: *"With a macular lesion like this on OCT, and their age, 37-year-old male, if they've got a high-pressure job or one that's likely to cause stress, we are at risk of central serous retinopathy or there's supposed to be a link. So, a bit more information about that. Obviously if you weren't getting that vibe, that they were stressed, then it might help your differential diagnosis."*

Patient-specific logistical factors also influence referral decisions. **Participant 15** highlighted the challenge of referring patients with dementia, noting that their ability to attend hospital-based assessments must be considered: *"So like you've seen fluid on a patient on OCT and you're there going, this patient's got dementia, they can't realistically attend the triaging at the eye hospital. Can we refer straight into EMac,* *um, not refer via EMac but refer straight into the injection clinic? So, to save her an appointment and stuff. In terms of cases where it's been a bit of an awkward one."*

Additionally, some optometrists modify their follow-up strategies based on the patient's ability to self-monitor. **Participant 10** described how their management plan may change depending on whether they believe a patient will actively monitor their vision at home: *"If I think the patient's quite savvy in the sense that they're going to use an Amsler grid or they're going to monitor their vision monocularly… potentially that would maybe dictate what I would do."*

7.3.2 Optometrist Factors

In addition to patient-related factors, optometrists' own professional perspectives, confidence levels, and approach to risk can influence how they interpret and act upon OCT findings. The interview findings highlighted several optometrist factors that can shape clinical decision-making, including their own perceptions of working within scope, willingness to take ownership of patient management, levels of risk aversion, and relationships with the HES. These factors affect how optometrists balance their clinical autonomy with the need for external validation to determine when onward referral is necessary.

Perception of Working Within Scope

A key consideration for optometrists when making management decisions is their perception of what falls within their professional scope. Optometrists in primary care practice often define their role as identifying whether a patient needs further medical attention, rather than managing conditions beyond their remit. **Participant 15** explained that within the context of primary care, their role is primarily about detecting whether a condition needs to be referred rather than making diagnostic and treatment decisions. They felt confident in determining whether a patient needed further assessment but acknowledged that beyond this point fell outside their scope. They described this distinction, stating: *"So within the context of primary eyecare, being able to pick up on something, if that makes sense. Particularly just pick up on something to the point of referral. There's very rarely a situation whereby I'm not comfortable, you know, going 'these needs seeing' or 'not.' If it was within the context of, does this person need another anti-VEGF issue and injection stuff, to be honest with you, no, because I'm not the person making the call. Or, you know, should this*

CSR be treated or should we just observe again? I think I'd probably be able to manage it relatively safely and do all right, but I'm not in that setup, so I don't. So, there's definitely an element of, 'Oh, I know what to do up to that point, and then beyond that is not my job, so I don't stress over it too much.'"

Other optometrists highlighted that their scope is not only determined by their job role but also by their own personal limitations in knowledge and experience. **Participant 11** reflected on how professional competence involves recognising when a case falls outside one's expertise. They described how they were comfortable admitting when they were uncertain and knew when to seek additional advice rather than make assumptions: *"I think the whole thing about being professional is knowing where your limitations are. So, if there's a scan that I'm not sure about, I think I'm okay knowing that it's a scan that I'm not sure about and to ask advice about. And I think that that's as important as being able to interpret them because knowing where your limitations are is one of the most important things."*

For some optometrists, not having a specialist qualification in medical retina influenced their decision to refer patients to secondary care. **Participant 3** described how, despite suspecting that hospital clinicians would also choose to observe a case, they would still refer it because they lacked the medical retina qualification that they felt was required to manage it independently: *"So I suspect they would just want to watch it as well. But this one, I'd rather the hospital watch it because I don't have the medical retina [qualification]. I don't know what else they might want to do."*

Taking Ownership of Patient Management

Closely linked to professional scope is the extent to which optometrists feel responsible for patient management within primary care. Some optometrists viewed themselves as having full ownership over their clinical decisions, ensuring continuity of care and taking responsibility for management rather than deferring decisions to secondary care. **Participant 6** reflected on this, explaining how when they were the primary clinician for a patient, they felt a responsibility to manage them independently where possible: *"If it was my patient, then I'd probably have to go along the lines of what I'd thought initially, just because I would be the one that'd be responsible for their care."*

Similarly, **Participant 18** expressed a desire to handle cases independently, acknowledging that the optometry profession inherently requires a high degree of autonomy: *"I would say maybe sometimes you feel yourself personally, oh, you know, I wish I was able to like deal with this case independently. Because the optometrist job role, you are predominantly quite independent, having to examine and make decisions yourself."*

The level of ownership taken by primary care optometrists varies based on experience, confidence, and external factors such as risk aversion and access to HES support.

Risk Aversion and Defensive Decision-Making

Risk aversion was a common theme among participants, with many expressing concerns about clinical responsibility and regulatory oversight. Some optometrists described a tendency to over-refer to ensure they were protecting their professional registration and avoiding clinical errors that could cause patient harm. **Participant 17** acknowledged that even when they were unsure about the nature of a retinal abnormality, they would err on the side of caution and refer the patient: *"To be honest, because he's with all these patients, if they are particularly him, if he has got reduced vision, he's young and I'm concerned about his macula, whether I know what it is or not, I am still going to refer him to cover myself."*

Similarly, **Participant 4** described how they had a default approach of prioritising patient safety, choosing to refer whenever they felt even slightly unsure: *"If my gut is saying to refer them in for that second opinion or if I think treatment's needed, I'd always err on the side of caution with that."*

Relationship with the HES

The extent to which optometrists interact with the HES can also influence their decision-making. Some practitioners have direct communication channels with ophthalmologists, allowing them to seek specialist advice before deciding whether to refer. Others may have limited access to HES input, leading to greater uncertainty and a higher likelihood of referral. **Participant 11** described how their access to HES support varies by region, explaining that in one area, they can easily email ophthalmologists for quick guidance: *"Where I'm not a hundred percent sure that it would need a referral into secondary care, but just shooting an email to them to say,* *what do you think of this? Do you think I should be sending this? Or should I be doing something urgently, or should I be, you know, is it fine to just re-scan in a couple of months?"*

In another region, **Participant 11** has access to a real-time consultant portal, allowing them to send images and receive secure instant feedback: *"We've got [...] consultant connect in [area] where you can sort of upload scans to this portal and it's like an instant messaging service between you and the ophthalmologist and you can get the app on your phone and it's all secure."*

Some optometrists also noted that receiving feedback from HES about unnecessary referrals had shaped their future decision-making. **Participant 14** explained how close relationships with HES professionals made them more mindful of referral appropriateness: *"They'd probably not be particularly happy with me because we do get told when they're not happy with the referral. I think because they know quite a lot of us personally, it makes us more conscious that we don't want to send things in that don't need sending."*

7.3.3 External Factors

In addition to optometrist-specific considerations, external factors such as funding constraints, continuity of care, variations in regional guidelines, and the structure of patient pathways play a significant role in shaping optometrists' decision-making processes. These factors, which are largely beyond an optometrist's control, influence whether they can monitor patients in primary care, how they determine appropriate management strategies, and whether they feel compelled to refer patients to the HES.

Funding and Continuity of Care

The ability to monitor patients in practice is often determined by the structure and policies of the optometric workplace, particularly in large multiple practices where multiple clinics run in parallel each day. Several participants working in these settings highlighted how this system makes it difficult for optometrists to arrange follow-ups for their own patients, limiting continuity of care. **Participant 10** described how the nature of multiple practices makes it challenging to ensure that patients are seen by the same clinician for follow-up, stating: *"I think in other settings outside of a multiple then you might have a bit more grace in that sense. But I think in a multiple where* *you've got lots of clinics, lots of people, it's in and out, I think it is more difficult. And also, the difficulty again with that is that who's following that up? You know, it's very difficult to follow your own patients up or more difficult to follow your patients up [..] If you're working in an independent, you're working in a single clinic, or maybe two, you are pretty sure that you might have to fiddle a couple of patients around, but you typically can see everyone you want to see again, whereas because there's such a, like a heavy flow of people going in and out of multiple practice, even if they're booked in to see you, if they rearrange for whatever reason, the routes in which that gets informed to you and how you follow that up and which days you are in versus what day they've rebooked them, it's much more complicated and I think less reliable."*

For many optometrists, the ability to follow up with a patient is also dictated by employer policies regarding appointment scheduling and funding. Some workplaces discourage early recalls for follow-ups, as these appointments do not generate revenue in the same way as new sight tests or dispensing opportunities. In contrast, practices that participate in schemes such as the Welsh Eye Care Service (WECS) or other enhanced service models receive financial support for monitoring patients within primary care, allowing clinicians to review patients more frequently without pressure from employers. These structural differences influence whether an optometrist chooses to monitor a patient in practice or refer them to the HES, as referral ensures that follow-up care will be conducted, even if the optometrist themselves is unable to facilitate it.

National vs Regional Guidelines

When managing patients, optometrists have access to national guidelines, such as those provided by The College of Optometrists, to guide their clinical decision-making. However, the interviews revealed that regional variations in guidelines can sometimes override national protocols, particularly in areas where local HES departments provide direct advice to optometrists. **Participant 14** described how their local HES, which serves a region with a high proportion of elderly patients, encourages optometrists to monitor stable cases in practice rather than referring unnecessarily. However, for specific conditions, such as central serous retinopathy (CSR), they are required to refer all cases urgently for fluorescein angiography:

"Also, because it's quite a small, like, the county we're in, there's a lot of old people,

they’re quite overwhelmed in the department because it’s quite small for quite a large region. They’re often quite happy enough for us to monitor things in practice. So, they’ll see something like this and say, ‘oh you need to keep seeing your optom’ and they’ll tell us how frequently they want us to scan them as well. But for example, with CSR they want us to refer everyone in urgently so they can do a fluorescein angiogram.”

In cases where local HES recommendations conflict with national guidance, optometrists tend to follow regional protocols, as these align with the referral expectations and management preferences of their local HES. These variations became particularly apparent when optometrists assessed example clinical cases, demonstrating how regional differences can shape decision-making and lead to differences in patient management across different locations.

Patient Pathways

The structure of patient referral pathways also plays a critical role in determining how optometrists manage suspected retinal conditions. Participants described a range of different referral systems, some of which remain paper-based, while others use email or digital portals to facilitate direct communication with the HES. Two participants working in different regions described how they still rely on fax machines to send urgent referrals: *“We have a pathway, a fast, um, sort of pathway for referring what we suspect to be wet AMD. So obviously we use, use that, you know, if um, we see something we suspect to be possible wet, then we send off, via a fax machine.”* - **Participant 12**

Other participants described more streamlined electronic pathways, where they can send referrals via NHS email, allowing for direct triaging by ophthalmologists. This system enables optometrists to seek specialist advice while maintaining clear communication with secondary care. **Participant 13** described how their regional HES allows them to email directly to the emergency department for urgent cases: *“Yeah. And then they welcome me emailing directly to the emergency department. So, whilst the emergency department email is basically triaged by ophthalmologists- so junior doctors. And then they triage it and it's quite easy for them to review scans and just reply by email. So, if they don't think something's necessary, um, they can ask me to tell the patient or they'll say, ‘oh, we'll tell the patient,’Or ‘oh yeah, we've* *brought them in earlier, don't need to tell the patient we're doing that.' So, it's very good clear communication."*

Similarly, **Participant 5** described an email-based pathway that allows them to seek a second opinion from a consultant, who can advise on whether a referral is necessary or if the patient can be monitored in primary care: *"Um, and it's their outpatients email, so it's not a particular referral platform, but you can either email them just for a second opinion, um, and the consultants reply back and say, 'oh, we think it's just this, can you see them again in practice in three months' time?' Or 'we'll have a look ourselves.' Uh, when I refer through, I always attach a referral letter with all the patient details. Yeah. So that they've got all the details, phone number, et cetera."*

Beyond email-based systems, some optometrists have access to dedicated referral portals, which allow them to upload OCT scans directly to the HES for specialist review. These platforms provide an additional level of communication and allow for more informed triaging of referrals. **Participant 11** described how their local HES has implemented a secure instant messaging service that enables optometrists to receive rapid feedback from ophthalmologists: *"We've also got a remote, um, oh, there was a case, actually, we use this, um, consultant connect in [specific area] where we, you can sort of upload scans to this portal and it's like an instant messaging service between you and the ophthalmologist and you can get the app on your phone and it's all secure."*

7.4 Summary

This chapter examined how optometrists reason through OCT-based decision-making in primary care practice. While some use OCT routinely and confidently, others adopt a more selective or cautious approach. Identifying the range of factors affecting patient management demonstrates how OCT interpretation is rarely isolated from broader clinical judgement, and that uncertainty is a common part of practice.

By introducing four practitioner profiles, this chapter highlighted that variation in behaviour is based on years since qualification, but is also shaped by access to specialist support, and personal confidence. The profiles also reflected different stages within Rogers' Diffusion of Innovations theory(215), from early adopters to more hesitant users, helping to explain differing rates and styles of OCT integration.

OCT may enhance decision-making, but it can also expose gaps in knowledge or reinforce existing anxieties, particularly where support structures are limited.

These findings suggest that decision-making with OCT is a dynamic and context-sensitive process, not easily reduced to binary choices or fixed pathways. Importantly, they suggest that increased access to imaging alone does not necessarily improve care.

These findings are discussed in chapter 10, in the context of their potential influence on the design and implementation of AI technologies to support OCT imaging interpretation.

Chapter 8: Interaction with Information

The way in which optometrists engage with information sources when assessing cases of suspected retinal abnormalities highlighted on OCT imaging depends on whether they are proactively expanding their knowledge or reactively seeking information in response to a specific clinical case.

The interview findings revealed that proactive and reactive information-seeking represent distinct strategies that optometrists use to manage clinical uncertainty. Proactive learning involves the pursuit of knowledge outside immediate patient encounters, often driven by professional curiosity, ongoing learning, and the desire to refine clinical expertise. In contrast, reactive learning occurs when an optometrist encounters a case that challenges their existing knowledge or confidence, prompting them to seek additional insights or validation in real time. The reactive approach is particularly relevant when optometrists are faced with ambiguous OCT findings or when clinical information contradicts their expectations, requiring further clarification before making a clinical management decision. Four main themes are presented in this chapter to cover the two types of learning:

1. **Information Needs and Focus Areas -** *what optometrists are trying to understand or clarify.*
2. **Learning Sources, Methods, and Evaluation -** *where and how optometrists seek information, and how they assess the usefulness, credibility, and accessibility of different sources.*
3. **Motivators for Learning -** *the internal and external drivers that encourage optometrists to seek out information.*
4. **Barriers and Enablers -** *the practical, social, and systemic factors that either support or hinder optometrists in their information-seeking behaviours.*

Two theoretical models are particularly helpful in framing how optometrists make sense of information. Kolb's Experiential Learning Theory (1984) describes learning as a cycle in which experience is followed by reflection, the development of broader concepts, and then active testing of these concepts in practice. This highlights how knowledge is not simply acquired but continuously adapted through experience. Schön's Reflective Practice Model (1983) adds a further dimension by distinguishing between reflection that occurs in the moment, while a decision is being made, and reflection that takes place afterwards. Both aspects are highly relevant to OCT image interpretation in optometric practice, where clinicians often need to manage uncertainty during patient encounters and later draw on those experiences to refine their approach. These models are introduced here to provide a foundation for later discussion in Section 8.3, where they are applied to understand how proactive and reactive information-seeking contributes to clinical learning and decision making in everyday practice.

8.1 Proactive Learning

In proactive learning, optometrists seek out new information, based on clinical scenarios that they have not yet encountered in practice. This proactive approach allows them to learn about specific OCT findings and acts as a training resource to prepare them. In this sub-section I discuss the aspects of proactive learning, divided into the four themes previously outlined.

8.1.1 Information Needs and Focus Areas

Proactive learning is often centred on building confidence in OCT interpretation and preparing for future clinical challenges. Several participants described the need to address gaps in foundational OCT knowledge. **Participant 19** shared, *"All my current CPD for the past three years has pretty much been all about OCT because it, you know, I wasn't taught this at university, so it's almost like I'm picking it up as I go along"*.

The Dual Nature of Proactive Learning

Proactive learning can involve mandated training, which ensures baseline competencies in OCT analysis and interpretation, and self-initiated efforts that reflect individual commitment to developing personal skills in assessing and managing clinical cases involving retinal OCT imaging. Both forms of proactive learning play an important role in helping optometrists' sense-making for OCT interpretation.

Mandatory learning serves as a structured and standardised approach to ensuring a baseline of knowledge and competency across the profession. Some participants described how completing specific training in OCT interpretation is a necessity that is either set out as a requirement for employment by their employer, or to be able to carry out eye examinations under specific local schemes such as the Minor Eye Conditions Services (MECS) schemes. The focus of this mandatory learning is to ensure all optometrists meet a minimum standard of proficiency and demonstrate foundational skills in OCT interpretation and participants recognised its importance in providing foundational skills.

Self-driven learning represents an essential component of optometrists' efforts to proactively enhance their knowledge and skills. Unlike mandatory training, self-directed learning allows optometrists to tailor their education to their individual needs, interests, and the gaps they identify in their knowledge. Participants reported that this is often motivated by the desire to improve clinical confidence and ensure high-quality patient care. Such self-directed efforts allow optometrists to engage in specialised learning opportunities that cater to their unique clinical challenges and areas of interest.

8.1.2 Learning Sources, Methods and Evaluation

Proactive learning among optometrists takes various forms, reflecting the diverse approaches to developing confidence and competence in OCT interpretation. Each method contributes uniquely to professional growth and the delivery of high-quality care.

Employer-led training

Employer-led training is often a starting point for optometrists learning to use OCT imaging. This training is often a structured set of learning materials with a method of demonstrating that the information provided has been understood, for example using a multiple choice questionnaire (MCQ). **Participant 13** described this as: "*The training that [employers] provide is online tutorials. There's a set of modules which all optometrists are asked to do as a core competency before starting or using that piece of equipment. So, you do the module, you sit an MCQ question and you have to pass a certain pass rate, maybe 80%."*

Some participants found initial training sessions provided by employers or equipment manufacturers helpful, as they offered a basic understanding of OCT and its applications. For example, **Participant 19** noted: *"We had modules online... that gave us a very basic understanding of what you're looking at."* Such training serves as an introduction, helping optometrists establish a foundation for further learning.

However, some optometrists felt that training was not always accessible or comprehensive enough. **Participant 17** shared how missing initial training due to maternity leave left them relying on colleagues for guidance: *“I needed someone in-store to show me... it’s very tricky to learn your way along.”*

Some participants expressed concerns about the variability in training quality and the lack of tailoring to individual knowledge levels. **Participant 9** highlighted how differences in optometrists’ skills can make mandatory training feel inadequate for those with more experience: *“There is a lot of difference in people’s ability to interpret OCTs... there’s no point in me sitting through a basic macular OCT lecture just to prove that I can do it.”* This underscores the need for training programmes that accommodate diverse skill levels, ensuring all participants gain meaningful value. While mandatory training plays a critical role in maintaining professional standards, participants also noted its limitations in addressing individual needs. **Participant 9** reiterated the issue with a one-size-fits-all approach: *“It’s a strange thing really, you know? You’ve got such a wide range of skills, and it’s hard to cater for everyone.”* The lack of tailored content leaves some optometrists feeling the training is redundant, while others find it insufficient for their needs.

Independent Learning

Self-directed CPD and specialised courses were frequently cited as key methods for proactively addressing gaps in knowledge. Many participants sought additional opportunities to enhance their understanding of OCT, often focusing on specific areas like certain retinal pathologies that they were less familiar with. **Participant 18** highlighted their proactive approach, saying: *“It’s been very self-directed... I always sign up to the eye hospital ones. […] I’m finding that relatively useful.”*

For others, pursuing formal qualifications such as postgraduate certificates proved to be a transformative step in their professional development. These qualifications not only enhanced their OCT knowledge but also instilled greater confidence in their clinical abilities. For example, **Participant 10** shared how obtaining a medical retina certificate had a significant impact on their confidence when interpreting more complex scans: *“I now feel fairly comfortable in what I interpret.”* This achievement highlights how targeted, advanced education can bridge gaps in understanding.

Many participants also discussed the role of online platforms and other educational tools in their self-driven learning. **Participant 1** highlighted the value of 'Optom Guru', a resource offering case-based and annotated explanations of OCT scans: *"It's an American website and it was the best learning tool that I've seen... you choose what you think it is, and then it explains with annotations on the OCT."* This resource provided an interactive way to develop practical knowledge of OCT interpretation, bridging the gap between theoretical knowledge and real-world application. Other participants relied on self-driven strategies such as reading manuals and searching for information on specific conditions. **Participant 2** shared their approach: *"I've downloaded a manual by Zeiss... I read through that periodically."* Similarly, **Participant 6** described using practice-based resources for case comparisons: *"There are also a couple of books in my practice that my supervisor had. Just physical copies of scans and I've read through those too, had a look at them."*

Some participants also dedicated time outside clinic hours to review patient scans in more detail. **Participant 1** shared: *"The first few days I used to stay at the clinic till 11 o'clock just reviewing them, going, 'What if I missed something?'"* These case-based methods allowed optometrists to develop a deeper understanding of OCT.

Collaborative learning

Collaborative learning was a valuable method for many optometrists, fostering a sense of community and shared growth. Participants frequently discussed the importance of peer support and networking for building their OCT knowledge. **Participant 19** described how sharing anonymised images with colleagues facilitated collective problem-solving: *"You can anonymise the picture and send it in, and you can have a lot of optoms discussing, 'Oh, what do we think it all is?'"* This collaborative approach allowed them to learn from the experiences of others while reinforcing their own understanding.

Many optometrists actively engage in informal learning through collaboration with colleagues as a method of proactive information seeking. This collaborative approach is particularly valuable in smaller practices, where optometrists share challenging or interesting cases they encounter. These discussions often focus on ambiguous OCT scans, allowing practitioners to discuss cases with peers who have diverse experiences and perspectives. By sharing knowledge optometrists learn from each other, enriching their clinical expertise and fostering professional growth. **Participant 3** highlighted the value of this type of collaboration, stating: *"Yeah, and if any of us have something interesting, we'll normally say, 'Oh, check the OCT for this because it's really cool.'"* This demonstrates how peers informally contribute to each other's learning by sharing noteworthy or complex cases which promotes curiosity and engagement with the technology.

8.1.3 Motivators for Learning

Proactive learning is driven by a variety of intrinsic and extrinsic factors that compel optometrists to deepen their knowledge and refine their skills. These motivators reflect the dynamic nature of optometry, where professionals must continuously adapt to evolving technologies, such as OCT, and the increasing complexity of clinical cases. Participants highlighted a range of factors that inspired their commitment to learning, from the desire to build self-reliance and confidence to professional growth and curiosity.

This theme explores the key motivators behind proactive self-driven learning, showcasing how these factors shape optometrists' approaches to enhancing their clinical expertise and improving patient care. By identifying and understanding these motivators, we can better appreciate the importance of tailored learning opportunities that support optometrists in meeting their professional development goals.

Self-reliance

Optometrists highlighted the importance of self-reliance in their clinical practice, particularly in the context of interpreting OCT scans. Proactive learning was a vital strategy for achieving this independence. Participants emphasised how engaging in additional learning opportunities helped them build the confidence and knowledge needed to reduce reliance on external resources, such as colleagues, ophthalmologists, or online forums.

Participants expressed concern about the risks of over-relying on external resources, which could undermine their clinical judgment and lead to complacency. **Participant 15** likened the reliance on ophthalmologists to support optometrists with clinical decisions to video-assist referee (VAR) technology in football, observing: *"I can see practitioners becoming complacent. I would liken it to VAR in football where the* *referee's too scared to make their own decision."* This analogy underscores the importance of the ability to make independent decisions, even in challenging cases. By engaging in proactive learning, optometrists ensure that they are prepared to manage cases autonomously, reducing the need for external validation. Overall, a proactive approach allows clinicians to anticipate difficult cases and build a stronger knowledge foundation, which they can rely on when immediate peer support isn't available.

Bridging Experience Gaps

Optometrists who lacked exposure to OCT during their training were motivated to 'catch up' and stay current with advancements in the field. As discussed in Chapter 7, optometrists who qualified over a decade ago often face the challenge of integrating OCT technology into their practice, as it was not part of their formal training. They therefore demonstrate a strong drive to bridge the gap between their clinical expertise and OCT knowledge. This process is characterised by proactive engagement with resources. For some, the absence of structured learning initially created discomfort when interpreting scans or encountering complex cases. As **Participant 1** noted, *"I find it shocking how people are just given a machine and they're like, 'Good luck.'"* This highlights the lack of early systematic support for OCT learning and the subsequent need for self-directed efforts to fill these gaps. **Participant 18** expressed a sense of unease when needing help, stating, *"Sometimes I'm a bit like, 'Oh, I wish I'd have been able to deal with that myself.' That doesn't help your own personal sort of anxiety about things."* These quotes illustrate how the desire for self-reliance and confidence can drive their proactive learning.

Professional Curiosity

Professional curiosity and growth encapsulate optometrists' intrinsic drive to deepen their understanding of OCT imaging and clinical decision-making. Across the transcripts, participants demonstrated an interest in exploring broader concepts, such as retinal structure and pathology, and engaging with complex or rare cases. This desire to expand knowledge and refine skills manifests in different forms of curiosity: general curiosity and reflective curiosity.

General curiosity refers to participants' natural fascination with clinical concepts and their proactive efforts to seek new knowledge. This type of curiosity often drives optometrists to explore interesting or unique cases beyond their immediate clinical needs. **Participant 3** shared their excitement about encountering unusual clinical cases, saying: *“He had [eye condition], and it was really cool to see the OCT because he had an entire, uh, half was swollen but half was normal […] and I was like, ‘Oh, that’s great.’ Not great for him, but really interesting clinically.”* This reflects their enthusiasm for using OCT technology to learn from complex pathologies and expand their clinical understanding. **Participant 19** also showed interest in learning from others’ interpretations, saying: *“I’d probably be quite interested to see what somebody might think that that spike is […] out of curiosity to see if anybody thinks what they think it is.”* This highlights their inquisitive approach.

Reflective curiosity describes the moments when optometrists critically evaluate their clinical decisions. This type of curiosity is rooted in a desire to learn from experiences and improve future performance and is particularly evident when participants reflect on cases they have already encountered in primary care, using them as opportunities for further learning. **Participant 15** reflected on how they proactively seek advice to learn from past cases: *“There are times where I’ve asked colleagues, just out of interest, just to see how they’d have managed it.”* This demonstrates how they use peer insights to re-evaluate their approaches.

Overall, proactive learning plays a crucial role in shaping optometrists' confidence and competence in OCT interpretation. Through a combination of employer-led training, self-directed learning, and collaborative engagement with peers, optometrists develop a well-rounded approach to expanding their knowledge. While mandatory training establishes foundational competencies, self-initiated efforts enable clinicians to tailor their learning to their individual needs, ensuring they stay current with evolving technology and clinical practices. Additionally, the motivators driving proactive learning highlight the profession’s commitment to continuous development.

8.1.4 Barriers and Enablers

Proactive learning, while largely self-motivated, is significantly shaped by systemic, organisational, and interpersonal factors. Participants described a range of circumstances that either hindered or facilitated their ability to seek out and engage with new information.

Access to tailored training

The importance of training quality and relevance was highlighted not only in this section, but also earlier under 'Employer-led Training'. Some participants felt that employer-provided training was “too simplistic” or not tailored to individual experience levels, making it less engaging or useful for more confident practitioners. Others appreciated employer training as a helpful foundation, particularly when entering practice with limited prior OCT exposure. This variation in experiences reinforces how the content and delivery of training can act as either a barrier or an enabler to proactive learning.

Participants reported an absence of structured OCT interpretation training suited to their current level of practice, particularly for those who were self-taught or trained before OCT was mainstream. While proactive learning is largely self-initiated, structural and systemic factors influence engagement. Barriers included lack of time, overly basic mandatory content, and absence of tailored training. Enablers included access to peer discussions, clinical materials, and digital learning tools. Peer encouragement and workplace culture also shaped engagement.

Some participants described how the ability to pursue formal postgraduate qualifications enabled deeper proactive learning with more in depth tailored training. In some cases, this was made possible through personal investment. **Participant 10** explained *“No I wanted to [fund it myself]. I guess I could twist [my employer’s] arm, but it isn't specifically funded and I wanted to do this for my own benefit and I don't want any employer to feel like I'm tied into anything”.*

For others, this was made possible through employer funding and endorsement. These opportunities provided structured, in-depth knowledge beyond what was available through informal learning or employer-led training, and were particularly valued by those seeking to enhance their clinical confidence and autonomy.

Supportive learning culture

Informal learning with colleagues, especially in teams where scan discussion was normalised, was consistently cited as an enabler for proactive learning. Some participants described reviewing scans together as part of daily practice and practices that encouraged ongoing discussion, provided informal mentoring, or embedded learning into workflows were seen as especially beneficial. In addition to support within practices, some participants also described how relationships with HES clinicians enabled proactive learning. For example, **Participant 6** noted, *"we're quite fortunate in our area where we've got some really good consultants that go through the cases with the optoms".* These interactions fostered learning beyond formal referrals and created opportunities for optometrists to learn from secondary care colleagues.

8.2 Reactive Learning

In primary care optometry, reactive learning occurs when practitioners encounter a specific case that requires targeted knowledge or clarification. Unlike proactive learning, which is more exploratory, reactive learning is case-driven and highly directed, focusing on obtaining precise answers to immediate clinical questions. Optometrists often engage in this process when interpreting OCT retinal images, particularly when they encounter ambiguous findings or need to validate their clinical decisions. This section explores the nature of reactive learning by examining the specific types of information sought to address case-specific challenges, the barriers and enablers influencing this process, and the various sources of information utilised to resolve clinical uncertainties effectively. These will be addressed independently under the same themes as those in section 8.1: Information Needs and Focus Areas, Learning Sources, Methods and Evaluation, Motivators for Learning and Barriers and Enablers.

8.2.1 Information Needs and Focus Areas

Optometrists described seeking targeted information to clarify what they observe on OCT imaging. This section explores the key aspects of this, focusing on three sub-themes: OCT Features, where optometrists seek to understand what a specific finding represents; Boundaries of Clinical Significance, where they determine whether a feature requires further action; and Patient Management, where they seek guidance on how to proceed based on the OCT findings and other clinical factors.

OCT Features

A key aspect of reactive information-seeking is identifying and differentiating between various retinal structures and abnormalities, particularly when certain features appear similar or ambiguous. Optometrists discussed reactively seeking information to interpret these specific OCT findings. For example, **Participant 7** highlighted the challenge of distinguishing between different types of pigment epithelial detachments (PEDs) on OCT imaging: *“I find it hard to diagnose between a fibrovascular PED and a normal sort of drusenoid PED.”* This demonstrates how optometrists may seek information to differentiate between features that share overlapping characteristics but have distinct clinical implications.

A common area of uncertainty was determining whether an OCT feature represents fluid, which can be a key indicator of pathology. **Participant 19** expressed this uncertainty, stating: *“Where we are with an OCT image, you know, something's there, you know, there's space. But what is the space? Is it telling it's fluid? Is it not fluid?”* Similarly, **Participant 5** questioned whether an observed feature was a true finding or an artefact: *“But I think sometimes you look at it and you think is that, is that fluid? Is it just a bit of a shadow cause the scan's not great quality.”* These examples highlight optometrists requiring additional information to differentiate between genuine fluid accumulation and artefacts or other anatomical or pathological features. This distinction is vital, as the presence of fluid often informs referral urgency and clinical management decisions.

Boundaries of Clinical Significance

In some instances, optometrists may confidently identify an OCT feature, such as fluid, but remain uncertain about its clinical significance. While the distinction between normal and pathological findings may be clear, there are cases where the implications of a finding are less straightforward. This uncertainty drives optometrists to seek further information to determine whether an observed feature requires action or can be safely monitored. **Participant 1** highlighted this uncertainty, stating: *“Essentially, I think […] when it's obvious, it’s easy, right? Unless somebody really is new to the technology or the profession, the question is, where does that boundary lie? Where are the edge boundaries of it? When is it concerning and when does it not even count, really?”* They further elaborated on this difficulty when discussing a case of suspected central serous retinopathy (CSR): *“Where are the boundaries? I,* *for example, saw a really, I called it a CSR, but it was really small. It was really, really small. Those boundaries of where are you just saying, where does the CSR start beyond being a tiny amount of fluid that we're going to ignore? Are you with me?"* This demonstrates how optometrists require further information to navigate clinical grey areas, ensuring they neither overreact to certain findings nor overlook indicators of disease.

Patient Management

In some cases, optometrists may be confident in identifying an OCT feature but remain uncertain about the appropriate management decision. Patient management can be complex, requiring the integration of multiple factors beyond the scan itself. The complexity of these management decisions was discussed in a previous chapter, which highlighted that these decisions rely on several other considerations.

Given these complexities, optometrists seek additional information to ensure they make the most appropriate clinical decision. **Participant 1** expressed the need for guidance on referral criteria, stating: *"And it's the stuff where I would say I'm desperate for help with is referral criteria now we have [OCT imaging in practice]."* Similarly, **Participant 11** highlighted the difficulty in determining whether certain cases require escalation, explaining: *"So there's quite a lot of cases up here where I'm not a hundred percent sure that it would need a referral into secondary care."*

Participant 12 described encountering a case with multiple pigment epithelial detachments (PEDs), raising the question of appropriate management: *"A patient that seemed to have quite a few, like multiple prominent PEDs, and you do come across those, but he seemed to have quite, quite a lot of them. And you think, oh, how's best to manage that?"* This highlights how, even when an optometrist is confident in identifying OCT features, uncertainty regarding best management practices may prompt them to seek further advice.

8.2.2 Learning Sources, Methods, and Evaluation

The effectiveness of an information source in supporting optometrists' decision-making depends on several key characteristics. This section explores the features that influence how optometrists select and use information sources, focusing on three key factors: Information Sources, which examines the different types of sources optometrists rely on; Evidence of Accuracy, which explores how optometrists assess the reliability of a source; and Rapid Access, which considers the importance of obtaining timely information in a busy clinical setting.

Information Sources

Optometrists use a range of information sources when reactively seeking additional guidance on OCT interpretation. The three main types of sources identified were HES links, colleagues, and case comparisons. The first two sources, HES links and colleagues, are covered in other sections and play a significant role in optometrists' information-seeking behaviours. This section focuses on the use of case comparisons as a strategy for gathering information.

Some optometrists compare their cases to existing images and descriptions found through various external sources, such as internet searches and textbook. This approach requires them to have an initial idea of what they believe the finding may be to conduct a targeted search. **Participant 11** described this method, stating: *"I did Google afterwards what vitritis looked like on OCT."* Similarly, **Participant 18** explained how they used Google to investigate an unfamiliar finding: *"Anyway, she ended up having choroidal folds. And it's the first time I've seen that, and I was like, oh, that doesn't look right. But I didn't really know what it was. So in that case, I actually Googled it cause I was like, is that... is it choroidal folds..?"* This highlights how some optometrists turn to online searches to compare their observations with known examples, using visual references to refine their interpretations.

Others prefer to consult physical resources, such as books and OCT atlases, to compare findings. **Participant 8** explained how they used a combination of resources to distinguish between potential pathologies: *"I just kind of just looked up different images, looked through some books and stuff and there's an OCT atlas PDF I think we've got, which we can scroll through. I was just trying to decide what other clinical features I would be looking out for to distinguish between the two different pathologies, just to see whether I could decide whether it was this or that or was it just a bit of both."*

While case comparisons provide valuable insights, they also require optometrists to interpret findings independently, as they do not involve direct consultation with another clinician. The effectiveness of this method depends on the availability of high-quality reference materials and the optometrist's ability to match observed features to documented examples.

Evidence of Accuracy

Optometrists frequently turn to their peers as sources of information for reactive learning, but this is only if they have confidence in their peers' expertise and background as evidence that they would be a reliable information source. The extent to which a peer is considered a reliable source often depends on prior experience working with them, their clinical setting, and their professional reputation. Many optometrists prefer to seek advice from trusted colleagues, particularly those who have mentored them during their training. For example, several participants, including **Participant 3, Participant 15, and Participant 16**, mentioned asking previous supervisors who had guided them in the early stages of their careers, valuing their expertise.

In some cases, experience in a hospital setting was viewed as a strong indicator of an individual's reliability as an information source for retinal OCT interpretation. **Participant 11** expressed confidence in consulting peers who worked in the HES stating: *"I've got some very clever friends I usually ask, who work at [eye hospital].* This highlights how optometrists may perceive colleagues working within the HES as having greater exposure to complex pathology, particularly in areas such as medical retina, making them a more trustworthy source of information.

Formal additional qualifications also serve as a marker of credibility when seeking peer advice. **Participant 18** described how a colleague's medical retina certificate increased their confidence in consulting them: *"As I say, my colleague, particularly in this instance, he's done a medical retina certificate. So, I think he is more sort of clued on to those sort of OCT scans and things."* This suggests that optometrists may be more inclined to rely on peers who have demonstrable advanced knowledge in a specific area of clinical practice.

However, not all peers are viewed as equally reliable. Optometrists only tend to seek advice from colleagues whose skills and expertise they personally know and trust. **Participant 16** described this distinction, explaining why they feel more comfortable consulting university friends than engaging with online forums: *"And you don't know, like at least with my friends, I know they did well in Uni and I know they're good at* *what they do, so they know their stuff. But if someone random answers on [forum], I don't know how much they know, they could be, they might not know any more, and it might not be the best advice to take."* Similarly, **Participant 10** expressed reservations about seeking advice from locum optometrists, as their clinical background and skill level may be unknown: *"I feel there's some people that I think are, are more useful than others as resources in that sense, or people that I think have better skills in that maybe, or be better confidence or understanding or interpretation of, of OCT perhaps than others. And we see a lot of locums and things like that, and it's always a bit more tricky with locums to know exactly where they're at."*

Other optometrists automatically assumed ophthalmologists were a reliable source of information based on their profession, often preferring forums that included ophthalmologists as contributors. This preference was reflected in participants' discussions about how they trust ophthalmologists' advice within online platforms or rely on direct connections to ophthalmologists as their primary source of support. **Participant 1** described this source of information as unquestionably credible, stating: *"And that one I basically take as gospel because it's an ophthalmologist. And I thought, I feel that an ophthalmologist knows and, and is, is slightly more invested than just looking at a [forum]."* This highlights how ophthalmologists' insights are perceived as inherently reliable, often taking precedence over other information sources.

These perspectives illustrate that while peer consultation is a valuable information source, optometrists carefully assess the credibility of the colleague before seeking advice. Rather than relying on general peer networks, they prioritise those with proven knowledge, direct clinical experience, additional qualifications, or a track record of accurate decision-making, ensuring that the information they receive is both trustworthy and clinically relevant.

Rapid Access

Another crucial aspect of reactive information-seeking is the need for rapid access to reliable information. Optometrists often face situations where timely clinical decisions are essential, particularly when they suspect a patient may have an eye condition requiring urgent referral to the hospital eye service (HES). In these moments, information must be readily available within a clearly defined timeframe to enable prompt action. The time-sensitive nature of these decisions is compounded by the high patient volume that optometrists typically manage daily, necessitating a focus on immediate, patient-specific information to ensure efficient and effective care. **Participant 20** emphasised the convenience of seeking advice from colleagues present on-site due to the immediacy required for clinical decisions. They explained: *"Normally just because they're on hand and it's just a quicker response. So, where I'd see my colleague walk past, I can just be like, oh actually can I just double check something with you quickly?"* This reflects their preference for immediate feedback when time is limited, ensuring that clinical decisions are made swiftly and efficiently.

Participant 2 highlighted the value of a specific forum for seeking advice from both optometrists and ophthalmologists. They noted: *"We do actually have a forum that's run by two ophthalmologists, and if you get any cases of OCT that you're not sure of, you can actually post it on there. And they very kindly reply to it from, honestly, anywhere from seven o'clock in the morning to 11 o'clock at night."* Conversely, this participant stressed that if they do not receive a rapid response, they will not wait and will instead seek alternative sources of support. They explained: *"When it's an urgent thing, I normally pop it on there... I wait 15, 20 minutes. I don't have all day to be waiting and I don't want to be taking that risk."* This highlights their reliance on rapid information sources for time-sensitive cases.

Many optometrists have noted that certain information sources, such as forums, are unsuitable for these high-pressure situations because they fail to provide quick, targeted insights. As **Participant 10** explained: *"I'm not sure how quick the feedback would be. So, it wouldn't probably be something that you could do during a test, be like, 'lads, what's going on?' Then they all swoop in. You probably wouldn't get an answer 'til the evening or the next day potentially. So, it wouldn't be useful in a clinical setting."* This underscores the importance of having immediate access to practical, concise information that can seamlessly integrate into the flow of a busy clinical setting. Optometrists require information sources that not only deliver accurate insights but also align with the urgent pace of primary care, enabling them to make informed decisions without delay.

8.2.3 Motivators for Learning

While proactive learning is often internally driven by long-term professional goals or curiosity, reactive learning is typically prompted by the demands of a specific clinical encounter. These motivators are immediate and situational, emerging in response to real-time uncertainty and the need for safe and accurate patient care.

Several participants described how uncertainty about OCT interpretation prompted them to seek a second opinion. As **Participant 11** explained, "*If there's anything that's very sort of marginal or borderline, I will ask a colleague to have a look*". This reassurance-seeking often reflected the pressure to make safe and accurate clinical decisions. **Participant 6** remarked, "*There are still things that come up and I have to ask colleagues or have a look up before I call the patient in if I still am unsure*".

Across the examples highlighted by participants, reactive learning was not simply about acquiring new knowledge but about reducing doubt, validating judgement, and feeling supported in moments of clinical ambiguity.

8.2.4 Barriers and Enablers

The extent to which optometrists can successfully seek and utilise information reactively is influenced by a range of barriers and enablers that impact their ability to access, interpret, and apply relevant information in clinical practice.

This section explores the key factors that influence optometrists' ability to seek information when faced with uncertainty, focusing on Competence, Referral Safety Net, and Environment and Systemic Factors.

Competence

The interview findings highlighted how concerns about clinical competence can act as a barrier to seeking information, as some optometrists feel hesitant to request assistance due to fears of either feeling less capable or being perceived as so by other clinicians. In some cases, this concern was linked to the judgement by clinicians at the HES. The prospect of appearing less competent in the eyes of ophthalmologists or experienced HES optometrists made some practitioners more cautious about reaching out for advice. **Participant 17** acknowledged this concern, stating: *"I don't know... it probably tarnishes my name at the eye hospital."* Similarly, **Participant 14** described how familiarity with HES professionals influenced their referral behaviour: *"Yeah, I think because they know quite a lot of us personally, um, it makes us more conscious that we don't want to [ask about cases] that don't need sending."* This suggests that optometrists working in close professional networks may feel increased pressure to appear confident in their clinical decisions, reducing their likelihood of seeking help.

The fear of judgement was not limited to interactions with HES professionals but also extended to peer interactions, particularly in public or professional settings such as forums. Some optometrists expressed reservations about seeking advice from large professional networks due to concerns about how their queries might be perceived. Instead, they preferred to consult trusted colleagues or close friends, as this reduced the risk of feeling judged. **Participant 3** illustrated this preference, stating: *"There's four optoms in our practice, including me. And then, um, we're also in friendship groups. Either mine from my uni days or theirs from their uni days. So, we can ask others, that we would want to ask, you know, that you don't feel too worried about making a tit of yourself with if you're wrong [laughs]."* This highlights how professional relationships and personal trust play key roles in determining where and how optometrists seek information.

Beyond concerns about judgement, some optometrists described a professional expectation of autonomy, particularly among more experienced practitioners or those working in independent practice. The belief that they should handle cases independently could discourage them from actively seeking advice, even when uncertain. **Participant 19** reflected on this mindset, stating: *"I think it's an element of I will personally have to make the decision anyhow."* This suggests that some optometrists may choose to proceed with their own clinical judgement rather than seeking information before making a decision.

These findings indicate that perceptions of competence, both self-imposed and influenced by professional networks, can act as a significant barrier to information-seeking. Whether due to concerns about external judgement, professional expectations, or a preference for maintaining autonomy, these factors can shape how and when optometrists choose to engage with additional information sources.

Referral Safety Net

The ability to refer patients to secondary care acts as a failsafe for optometrists when faced with clinical uncertainty. While referrals are a necessary part of patient care, in some cases, the availability of this option reduces the motivation to seek additional information, as referring the patient removes the immediate need for further clinical decision-making. When an optometrist is unsure about the significance of an OCT finding, referring the patient may be seen as the safest course of action. **Participant 2** acknowledged how uncertainty often leads to referral, stating: *"If in doubt […], I will just use my gut instinct and go with that. Which usually, but not always, ends up in a referral."* This highlights how, rather than spending time seeking additional information, the default action can be to refer, particularly when the optometrist feels unsure.

Participant 19 described how OCT technology can sometimes contribute to unnecessary referrals, as optometrists may become overly cautious when interpreting findings: *"Some referrals in my opinion don't need to be sent and people look at OCT and panic and send it [...] some of my team might refer more because of OCT."* The presence of a referral pathway provides an easy alternative to in-depth information-seeking, as erring on the side of caution ensures that any potential pathology is assessed by secondary care.

For some optometrists, rather than investing time in gathering further clinical insight, the option to refer provides an immediate resolution to uncertainty. **Participant 17** acknowledged this tendency, stating: *"There's no, um, there's no real clinical person I can ask. So I tend to over refer in that case."* This highlights how the ease of referring a patient removes the incentive to engage in information-seeking, as the responsibility for clinical decision-making is effectively transferred to secondary care. While referrals are essential for patient safety, the presence of a referral safety net can discourage optometrists from engaging in information-seeking behaviours that could help them make more independent and confident clinical decisions.

Contextual and Systemic Factors

One significant barrier to information-seeking for some optometrists is the inability to share OCT imaging when seeking advice on ambiguous cases. In many instances, this limitation stems from resource constraints, where no formal systems exist to facilitate the secure uploading and sharing of images for external review. Without structured pathways to seek remote input, optometrists may be left to rely solely on their own clinical judgement or attempt to describe findings verbally, which is less effective than sharing the image itself.

In some cases, optometrists working in larger optical chains may have access to internal forums that allow them to seek advice from colleagues. However, despite having access to such platforms, some practitioners remain reluctant to post cases online due to concerns about confidentiality and data protection. **Participant 13** highlighted these concerns, stating: *"I'm not happy with sharing images, but I do in passing and I have seen people that share images, so that's something I'm mindful of, of the GDPR and the protection within it."* This suggests that while internal forums could act as an enabler for information-seeking, perceived risks associated with data security and compliance regulations may act as a deterrent for some optometrists.

Another workplace-related factor influencing information-seeking is whether optometrists work alone or within a team. Those based in independent or smaller practices often lack immediate access to colleagues, meaning they do not have someone readily available for case discussions. In contrast, optometrists working in settings where colleagues are on hand may benefit from real-time discussions and second opinions, reducing the need to seek external advice.

Additionally, direct links with the HES can act as a facilitator for information-seeking. Some optometrists have established formal pathways to communicate with HES clinicians, allowing them to obtain specialist input efficiently. Others rely on informal connections with ophthalmologists they have worked with previously. As highlighted in earlier sections, HES ophthalmologists are often regarded as the most reliable source of information, meaning those with access to these professionals are more likely to seek advice in cases of uncertainty. For some optometrists, structured shared-care arrangements with ophthalmologists provide direct access to specialist input, reducing the need for independent decision-making. **Participant 11** described how working in a setting with private shared-care agreements facilitated information-seeking: *"The practice up here, uh, they do quite a lot of sort of shared care with, uh, private shared care with ophthalmologists. So we did have a couple of ophthalmologists on hand to just send scans to. Um, so there's quite a lot of cases* *up here where I'm not a hundred percent sure that it would need a referral into secondary care, but just shooting an email to them to say, what do you think of this? Um, do you think I should be sending this?"* This highlights how optometrists with access to direct communication pathways are more likely to seek specialist advice, leading to more informed referral decisions and potentially reducing unnecessary referrals.

Informal one-to-one support from ophthalmologists can also be highly valued, particularly when a reliable contact is consistently available. **Participant 1** expressed the benefits of having a responsive ophthalmologist to consult, stating: *"The ophthalmologist is, um, yeah, available on that and has been every time I have had a, had a query. Um, and I don't know what their working hours are, but I've always, I, I've always tried to make sure it's, I get in my queries before six and then I will normally get a reply. Um, and on a personal note, it is incredible to have that support."* This highlights how timely access to specialist input can enhance clinical confidence, allowing optometrists to validate their decision-making in real time.

Environmental and systemic factors play a crucial role in shaping optometrists' ability to seek information effectively. Limitations in image-sharing infrastructure and concerns over data protection can hinder access to external advice, forcing practitioners to rely on verbal descriptions or independent judgment. Workplace setting also influences information-seeking, with those in smaller practices facing greater challenges compared to those with in-person colleagues or established links to HES clinicians. Access to structured communication pathways, such as shared-care agreements or informal ophthalmologist support, facilitates specialist input, enhancing clinical confidence and potentially reducing unnecessary referrals.

8.3 Applying Kolb's and Schön's Models to Sense-Making in Optometric Information-Seeking

As optometrists engage in proactive and reactive information-seeking, the next crucial step is how they integrate newly acquired knowledge into their clinical practice. This integration process can be considered 'sense-making' in OCT interpretation, which involves not only acquiring information but also interpreting, integrating, and applying it to refine clinical decision-making. Two key models provide a useful framework for understanding how optometrists make sense of new knowledge: Kolb's Experiential Learning Theory (1984) and Schön's Reflective Practice Model (1983). These models have been adapted for this context by combining the model ideas to explain how optometrists engage in both proactive and reactive learning, using reflection to continuously refine their clinical reasoning (Figure 19).

Kolb's model describes learning as an iterative cycle, consisting of four stages: concrete experience, reflective observation, abstract conceptualisation, and active experimentation. This model is particularly relevant to how optometrists incorporate new knowledge into their decision-making over time, whether through structured learning or direct patient encounters. It highlights that learning is not a linear process but a continuous cycle, where new experiences shape future decision-making. In optometric practice, both proactive and reactive information-seeking contribute to the ongoing refinement of clinical reasoning.

Schön's model adds further depth by distinguishing between 'Reflection-on-Action' and 'Reflection-in-Action'. Reflection-on-Action aligns with proactive learning, where optometrists seek knowledge outside immediate clinical encounters to enhance their baseline OCT understanding and develop frameworks for recognising and interpreting OCT findings. Reactive information-seeking, while primarily linked to Reflection-in-Action, also connects to Reflection-on-Action. This is because when optometrists seek information in response to an ambiguous clinical case, they must quickly interpret, evaluate, and apply new knowledge while managing the patient in real-time, which is Reflection-in-Action. However, the learning process does not stop at the point of decision-making. The knowledge gained from these interactions is often revisited and reflected upon after the case, contributing to Reflection-on-Action by helping optometrists adjust their understanding, refine their approach for similar cases in the future and readjust their new baseline OCT knowledge. Through this process, reactively acquired knowledge is not only used in the moment but also assimilated into long-term learning, reinforcing clinical competence and confidence over time. This section explores how these two models explain the process of sense-making in optometry. By applying Kolb's and Schön's frameworks, we can better understand how optometrists engage with, reflect on, and apply new information, ensuring that their learning is iterative, experience-driven, and continuously shaped by both immediate and past encounter.

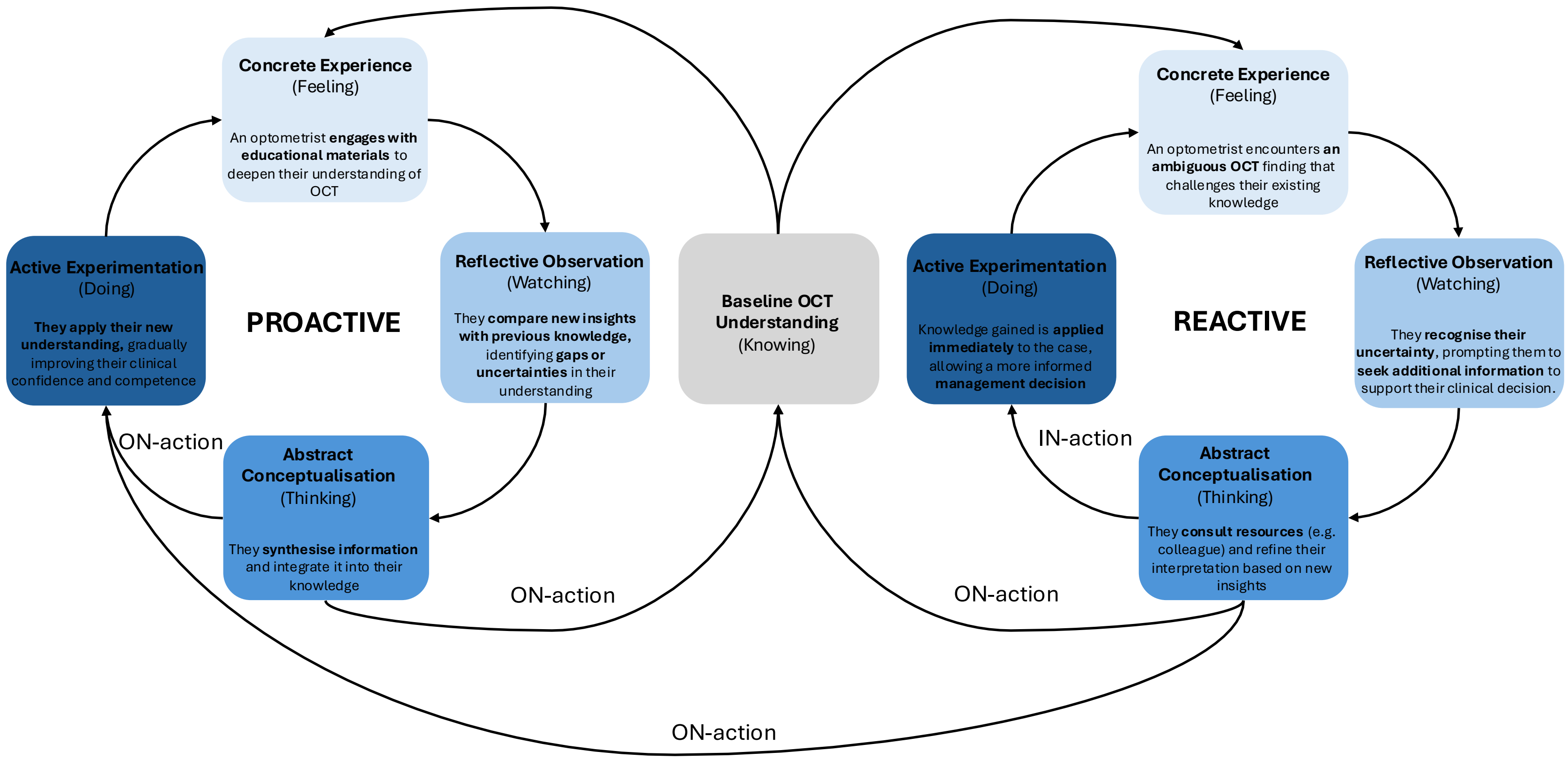

Figure 19: Adapted models for 'Kolb's Experiential Learning' with separate cycles for reactive and proactive learning and integration of Schon's reflective practice model.

8.3.1 Proactive and Experiential Learning

As discussed, proactive information-seeking reflects a deliberate effort to expand clinical knowledge before encountering an immediate patient case. In Kolb's framework, this aligns with a structured learning process, where optometrists actively engage with educational resources, reflective practice, and applied learning. The following sub-sections outline these stages of Kolb's learning cycle in the context of optometry.

Concrete Experience

Proactive learning begins with direct engagement with educational materials that provide new insights into OCT interpretation and clinical decision-making. Optometrists actively seek out knowledge through resources such as:

- Clinical guidelines that outline the latest diagnostic and management protocols.
- Professional development courses and CET (Continuing Education and Training) to stay updated on evolving clinical standards.
- Case discussions with colleagues and expert panels, allowing for knowledge exchange and exposure to diverse clinical experiences.
- Case studies from online resources and textbooks, which provide a deeper understanding of pathological patterns and differential diagnoses in OCT interpretation.

By exposing themselves to a range of learning materials, optometrists expand their clinical repertoire, preparing themselves for more complex and ambiguous cases they may encounter in practice.

Reflective Observation

After engaging with new information, optometrists critically reflect on how it compares with their existing knowledge and experiences. This stage involves:

- Identifying areas of uncertainty where their previous understanding may have been incomplete.

- Recognising discrepancies between prior assumptions and newly acquired insights.
- Evaluating case examples and considering how similar findings were interpreted or managed in past clinical encounters.

For example, an optometrist who learns about subtle indicators of pathology on OCT scans may reflect on previous cases where they were uncertain about particular findings. This process strengthens pattern recognition and encourages practitioners to re-evaluate their diagnostic thresholds, improving their ability to distinguish between normal variations and early signs of disease.

Abstract Conceptualisation

At this stage, optometrists synthesise their learning by integrating new knowledge into their broader clinical framework. This involves:

- Reconstructing their mental models of OCT interpretation, incorporating newly acquired insights.
- Refining their diagnostic approach, considering how updated information can improve accuracy and efficiency in clinical assessments.
- Adjusting referral and management decisions, ensuring that evidence-based guidelines and best practices are consistently applied.

This shift in understanding influences not just how they interpret images but also how they communicate findings and make patient management decisions.

Active Experimentation

The final stage of Kolb's learning cycle involves applying new insights in real-world practice, allowing optometrists to test their updated understanding in a clinical setting. This stage is critical for:

- Enhancing confidence and competence, as optometrists see the impact of their learning on patient care.
- Validating new knowledge, reinforcing what works well and identifying areas that may still need refinement.

- Further reflection and continuous learning, as real-world application leads to new questions and deeper inquiry.

Over time, their diagnostic accuracy improves, and they become more confident in distinguishing pathological from benign findings. This iterative learning process ensures that proactively sought knowledge is not simply accumulated but actively incorporated into clinical decision-making, allowing optometrists to refine their interpretation of OCT findings over time.

8.3.2 Reactive and Experiential Learning

Unlike proactive learning, which builds knowledge gradually, reactive learning is driven by clinical ambiguity and requires optometrists to engage in Kolb's experiential learning cycle in real time. This process allows them to rapidly assess, interpret, and apply new knowledge, ensuring that their clinical decision-making is timely and well-informed.

Concrete Experience

The reactive learning process begins when an optometrist encounters an ambiguous OCT finding that challenges their existing knowledge or expectations. These cases often present diagnostic uncertainty:

- The optometrist identifies a finding that does not match their previous experiences, prompting them to question their diagnostic certainty.
- There may be contradictions between their initial clinical impression and the OCT scan, requiring them to seek clarification before making a referral or management decision.
- The need for timely action differentiates reactive learning from proactive learning, as decisions must be made about the case promptly, to ensure patient safety.

Reflective Observation

At this stage, the optometrist recognises their uncertainty, leading them to reflect on what they know and what they need to clarify. Unlike proactive learning, where reflection occurs after structured learning activities, reactive learning requires optometrists to pause and assess their knowledge gap in real time.

- Optometrists must determine whether their current understanding is sufficient or whether they need additional information to support their clinical judgement.
- They may consider previous cases with similar findings, assessing whether past experiences provide useful insight.

Abstract Conceptualisation

Once the need for further information is established, the optometrist engages in rapid knowledge acquisition, seeking insights that will immediately inform their decision-making. This stage involves:

- Consulting colleagues or supervisors, particularly those with expertise in OCT interpretation.
- Utilising HES links where available, as hospital-based professionals are often considered the most reliable source of information.
- Referring to clinical guidelines, textbooks, or OCT atlases, particularly when faced with an unfamiliar pattern or feature.
- Searching for case comparisons or published literature to validate their observations.

At this point, the optometrist refines their interpretation, integrating the new insights with their existing clinical framework. This step is essential in ensuring that reactive learning does not simply address the immediate case but also contributes to broader clinical development.

Active Experimentation

The final stage of the experiential learning cycle involves applying the newly acquired knowledge to the case at hand, allowing the optometrist to make a more informed referral or management decision. This phase requires:

- Synthesising the information quickly to ensure that the decision is both timely and evidence-based.
- Communicating findings confidently to the patient and, if necessary, explaining the rationale for referral or monitoring.

- Evaluating the effectiveness of the new knowledge, considering whether it improved diagnostic certainty or led to a better understanding of the case.
- Further reflection and continuous learning, as real-world application leads to new questions and deeper inquiry.

Although reactive learning is often seen as case-specific, its impact extends beyond the immediate situation. Lessons learned through reactive information-seeking contribute to long-term clinical development, influencing how optometrists approach similar cases in the future.

8.4 Summary

This chapter showed that optometrists use two distinct but complementary learning strategies when interpreting OCT in primary care: proactive learning, where they build knowledge outside patient encounters, and reactive learning, where they seek targeted information in response to a challenging case. Across both approaches, optometrists' information needs centred on identifying OCT features, judging clinical significance, and making management decisions, with choices of information sources shaped by credibility, accessibility, and the need for rapid reassurance. Barriers such as time pressure, confidence concerns, limited image-sharing infrastructure, and inconsistent local guidance influenced when and how information was sought, while supportive workplace cultures, trusted colleagues, and strong links with HES enabled learning. Finally, the chapter framed how newly acquired knowledge becomes integrated into practice through sense-making, drawing on Kolb's experiential learning cycle and Schön's reflective practice to explain how optometrists refine OCT interpretation and decision-making over time.

Chapter 9: Human-Computer Interaction and the Design of AI for Optometric Practice

This chapter extends from the findings in Chapters 7 and 8 by focusing specifically on how AI may be integrated into primary care optometry, with particular attention to the design, usability, and HCI aspects of AI-CDSS. Again, drawing on the qualitative data from semi-structured interviews and think-aloud clinical case assessment, this chapter explores how such tools are perceived by optometrists, how interactions with AI can be shaped by initial expectations and trust, and how future systems might be designed to better meet optometrists' information needs.

Chapters 7 and 8 established that optometrists regularly encounter clinical uncertainty when interpreting OCT imaging and often seek reactive information in response to ambiguous cases. Participants described a range of sources they might turn to, including websites, forums, colleagues, and professional guidelines. However, some discussed how these current options were not always readily accessible or required time and effort that was incompatible with the short duration of a typical patient appointment. AI-CDSS systems may be used to address this challenge by offering instant, standardised, and potentially ‘expert-level’ support. However, as this chapter will show, optometrists' acceptance and use of such tools can be shaped by multiple factors beyond diagnostic accuracy including perceived usefulness and alignment with their working practices and values.

9.1 Attitudes Towards AI and Shaping Interactions

Most participants (n=12) showed initial optimism (n=10) or neutrality (n=2) towards AI in optometry before being exposed to the demonstration system. This initial positive or neutral stance significantly influenced how they interacted with and reacted to the AI system during the demonstrations. The ‘optimistic’ participants generally accepted the AI’s outputs that were presented to them, often defaulting to the assumption that the AI was correct, even when it contradicted their own assessments. This pre-existing belief in AI’s potential seemed to predispose them to trust the system’s suggestions, even if they had some criticism of the outputs.

To avoid obscuring the broader thematic patterns, detailed participant accounts are provided in **Appendix 3.4**. In this section, key trends across groups are summarised, while retaining selected illustrative examples in the main text to demonstrate how these patterns were expressed in practice.

9.1.1 Optimistic and Neutral Participants

The majority of participants (n = 12) approached the demonstrations with either optimism or neutrality towards AI. A common feature of this group was their general acceptance of the AI system's outputs, often without substantial challenge. Participants who were already positive about AI tended to express trust in its diagnostic and management suggestions, even when these conflicted with their own judgments. For example, **Participant 1** immediately declared they "loved it" upon seeing the system, despite recognising that the AI had missed certain features. Similarly, **Participant 7** explained that they began to "agree" with the AI's suggestions as soon as they were displayed, illustrating how prior optimism translated into acceptance.

Across the group, segmentation maps were consistently highlighted as the most useful aspect of the AI system. Several participants explained that the maps reassured them when uncertain and made complex scans easier to interpret. **Participant 5** described the maps as particularly valuable when image quality was poor, using them as a "backup" to confirm their own impressions. **Participant 14** reported that agreement with the AI boosted their confidence, whereas disagreement made them doubt their own decision-making.

Neutral participants, while less overtly enthusiastic, still engaged with the outputs in a largely accepting way. They rarely challenged the AI's outputs, instead treating them as an additional perspective that could increase comfort with decisions. For instance, **Participant 17** reported feeling "more comfortable" with their management choice after reviewing the AI's output for case 3, even though they did not fully rely on it.

Overall, initial optimism or neutrality towards AI shaped how participants interacted with the system. Their predisposition to trust the technology led to a favourable reception, with the AI viewed as a supportive tool that could enhance practice and reduce uncertainty, particularly for less experienced practitioners. However, this tendency to accept outputs at face value also suggests a risk of over-reliance, especially when confidence in OCT interpretation is low.

9.1.2 Sceptical Participants

In contrast, a smaller group of participants (n = 8) were consistently sceptical of the AI system. Their scepticism was evident both before and during the demonstrations, with participants questioning the reliability, accuracy, and added value of AI in clinical decision-making. Rather than being reassured by the outputs, they often dismissed suggestions that conflicted with their own assessments. For example, **Participant 3** stated outright that “a person is always going to be more accurate,” while **Participant 6** explained that if the AI disagreed with them, they simply assumed it was wrong.

Even when the AI agreed with their assessments, sceptical participants frequently downplayed its value. **Participant 10** described the AI as unhelpful because it did not provide “any new information” beyond what they already knew. Similarly, **Participant 12** noted that while segmentation maps could be reassuring, they still doubted the AI’s diagnostic accuracy and were critical of its broad management suggestions. Concerns also centred on the risks of over-reliance: **Participant 9** worried that heavy reliance on AI could erode clinical skills, while **Participant 11** raised fears that missed urgent conditions could cause harm.

Overall, sceptical participants highlighted some of the challenges of introducing AI into optometry. Their responses reflected a mistrust of the technology’s reliability and a concern that it could diminish the role of optometric professional judgment. This group demonstrated a more guarded approach to human-AI collaboration, underscoring the importance of accuracy, transparency, and clinician control in the future deployment of AI systems.

9.2 Comparing AI Outputs

This section explores how participants engaged with the three different forms of AI-CDSS support: segmentation maps, diagnostic suggestions and management suggestions. These outputs provide distinct types of assistance. Feedback during the AI demonstrations offered insight into when and why each output was perceived as helpful or problematic, reflecting a range of expectations and contextual needs that arise in real-world optometric clinical decision-making.

9.2.1 Segmentation Maps as an Isolated Information Source

Some participants described segmentation maps as a particularly helpful element of AI output, especially when used independently from diagnostic or management suggestions. In situations where they were uncertain about specific OCT features, segmentation maps provided an additional layer of information to support their clinical decision-making. These maps were often viewed as the most valuable part of the AI system, largely due to the way they simplified OCT interpretation. Participants appreciated how the segmentation overlays helped distinguish between anatomical structures and pathological features, aiding them in more confident and accurate assessments.

*"Um, I would say, I think you could just use the AI segmentation on its own if you were confident with different types of pathology [...]. I think you could use the AI segmentation without the other two bits." - **Participant 14***

The positive view of the segmentation maps was aligned with the sources of uncertainty that participants described when prompted to recall occasions in practice when they needed additional information or support regarding OCT findings (Chapter 8). For several optometrists, a frequent information need was the interpretation of a specific OCT observation, predominantly involving the determination of fluid presence on the OCT image.

*"I still find it challenging to distinguish between fluid and [another pathological feature]. That is quite tricky." - **Participant 17***

Additionally, this source of uncertainty was displayed when participants assessed the example clinical cases, as they queried specific points on the OCT image. For example, in case two, 16 of the 20 participants were unsure about whether a specific area of the retina was fluid or not (Figure 20).

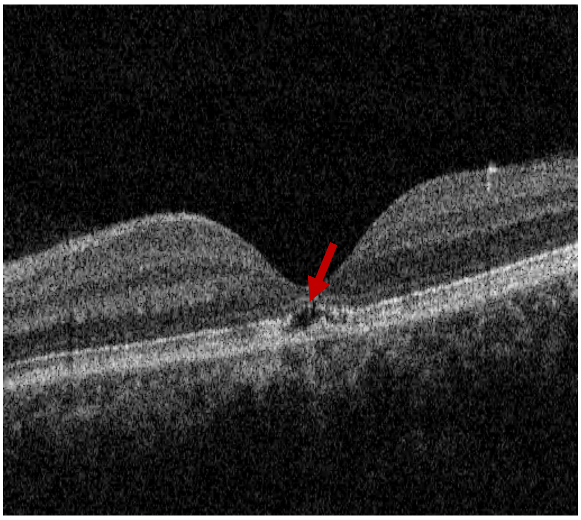

Figure 20: Macular OCT slice from Case 2. The red arrow highlights the region where participants questioned the presence of fluid.

Although participants were generally positive in their view of segmentation maps, some were concerned that the maps did not always detect the most subtle features of the OCT imaging and that these features were important parts of the OCT that were 'missed' by the segmentation. These concerns highlighted improvements that would be needed, especially if the segmentation maps were to be deployed as the only part of the example system's three outputs. For example, in Figure 21, the circled hyper-reflective part of the OCT scan was a point that optometrists were unsure about for case 1 and felt that by the segmentation map not classifying this specific point, the output did not help them to interpret the scan any better than without AI support.

These findings highlighted that in certain situations, the example segmentation maps may not distinguish between specific retinal features that are most important to the user when assessing a patient.

"So, in the first case, that area that I was querying, the top of the volcano with the brighter bits coming out, for example, I know that's a terrible description, but I would, if I could hover over that on the OCT and have a magnified view of that on the segmentation." - ***Participant 17***

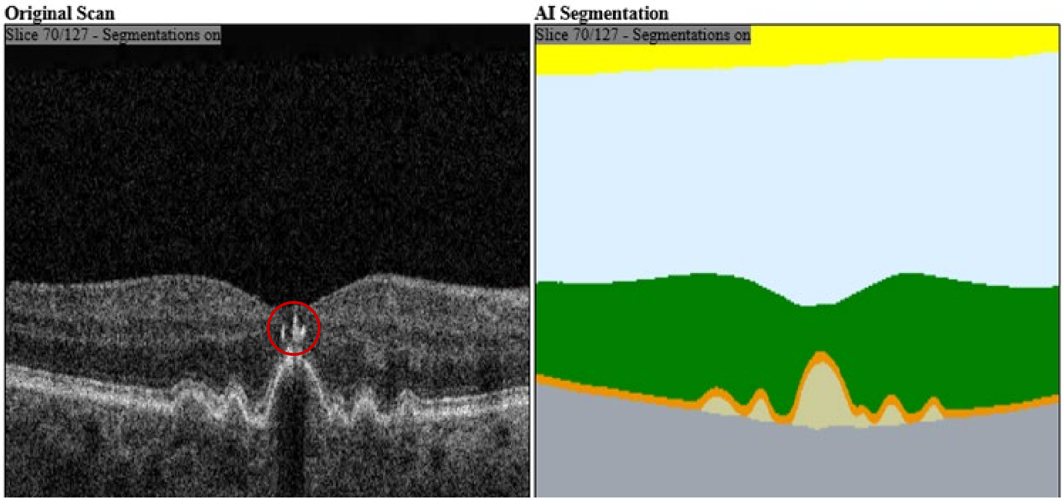

Figure 21: Case 1. Example of a slice where the segmentation map did not display areas of hyper-reflectivity (red circle) when colour coding the OCT scan.

9.2.2 AI as a Holistic Tool

The second way in which AI could support optometrists is to also suggest a possible diagnostic and management decision to help them when considering the 'whole picture'. As discussed in Chapter 7, these decisions are made after the eye examination is performed and OCT scan has been analysed. Outputs from an AI tool for this purpose would mimic the clinical decision-making, latter stages of the patient appointment journey, despite being provided with only the OCT findings.

The prominent theme during the clinical decision-making part of the study, however, was that diagnosis and management of patients were determined by the assessment of a multitude of contributing factors in addition to OCT findings (discussed in Chapter 7). For all three cases, but particularly for case 2, optometrists' diagnosis and management of the patient would be guided by a detailed patient history and symptoms, rather than the clinical findings alone.

"Is he a welder? I'd like to know a bit more about his lifestyle." - ***Participant 7***

"I would need to know how long the symptoms have been like that because if it's just for a diagnosis, then it would be a routine referral. If it's something more, um, recent sudden onset, then I'd be looking at ringing the hospital. I would want a diagnosis a bit more, more urgent if the symptoms were sudden." - ***Participant 4***

As discussed in detail in Chapter 7, participants highlighted that local advice for the management of ocular conditions varies greatly between different regions and compared to the official College of Optometrists' clinical management guidelines. This variability in local guidance highlights the lack of standardisation that is currently available and leads clinicians to often follow advice given to them from their local hospital. The importance of these contributing factors perhaps explains why of the three outputs, management outputs were considered the least useful and, for some optometrists, they felt that these suggestions should not be included in an AI-CDSS at all.

"I do not think you should put a management suggestion at all. It's too ambiguous and referral guidelines locally are very different." - ***Participant 9***

The significance of this perspective on management recommendations lies in the fact that, before being exposed to AI-generated information, numerous optometrists shared instances of seeking guidance specifically on patient management, mainly the necessity and urgency of referrals. This pattern of behaviour indicates that obtaining management insights is frequently a pivotal aspect of their information search when grappling with the interpretation of challenging OCT scans. In these scenarios, optometrists appeared to be confident in their interpretation of the OCT findings and utilised their information sources to determine appropriate patient management strategies, with the emphasis placed on devising a plan rather than diagnosing or interpreting specific OCT features.

"So, I think about, um, there was um, a patient that seemed to have quite a few, like multiple prominent, um, [pathological features], and you do come across those, but there were quite a lot of them. And you think, oh, how's best to manage that?" - ***Participant 12***

However, offering an AI management suggestion solely based on the OCT scan was not regarded as a satisfactory form of support for the example cases.

9.2.3 Perceived Disconnect Between Outputs

Some participants perceived inconsistencies within the AI outputs, noting that different components of the system did not always appear to align. In particular, they described instances where the segmentation maps highlighted specific features that were not acknowledged or reflected in the accompanying diagnostic suggestions.

"Interesting that it doesn't say ERM here [diagnostic suggestion] as well, given that there is an ERM and it even has it on the AI segmentation. But it didn't decide it was worth noting up here [diagnostic suggestion]." - ***Participant 10***

In this instance the segmentation map had highlighted the presence of an epiretinal membrane, which the participant felt was correct, but the diagnostic output did not include ERM as a suggested condition. This discrepancy between the segmentation and diagnostic outputs reflects a potential limitation in how the diagnostic model was structured, which was discussed in section 5.3. Due to different thresholds for pathology detection 'reference standards' between the segmentation maps and diagnostic suggestions, there are occasionally discrepancies between the outputs. From a clinical perspective, ERM would reasonably be expected to appear in the diagnostic output for this case, so participants' concerns about misalignment were justified.

The issue of misalignment was most frequently raised in relation to management suggestions, particularly in case 1, where participants felt that the recommendations did not correspond with the clinical findings displayed in the segmentation map or diagnostic outputs. For some, this prompted speculation about the underlying logic of the system.

"It's interesting that there's such a low percentage for observation but maybe that's because it doesn't rely on other factors such as vision. Like, it's just going on OCT alone. And so, it knows it's not normal, therefore you probably have to do something. I don't know how the AI is structured, but that's my interpretation of it. Like, this is saying you have to refer essentially." - ***Participant 10***

In fact, this interpretation was largely accurate as the example AI system was designed to generate outputs solely from OCT data and did not incorporate other clinical variables such as visual acuity. As a result, management suggestions sometimes leaned towards referral even in cases where observation could also have been appropriate if wider clinical information were considered.

Others interpreted the inconsistencies as indications of the wider assumptions built into the AI. **Participant 12**, for instance, reflected that the management outputs might account for factors such as disease progression or variation in referral pathways across regions.

*"But it's sort of suggesting referring, whether because it thinks there is potential for something to change, and yeah, 'cause there are also different referral routes and referral things across the whole country." - **Participant 12***

While this was a thoughtful interpretation, in practice the AI system does not incorporate contextual factors such as regional referral patterns. Instead, its recommendations are based on probabilistic associations learned from OCT training data. Participants' reflections therefore highlight how clinicians attempt to "fill in the gaps" when outputs do not align with their expectations, sometimes attributing the system with more contextual awareness than it possesses.

Taken together, these views illustrate how perceived inconsistencies in the AI outputs did not simply lead to doubt but also encouraged participants to actively reflect on how the system might be structured. While some of their interpretations were accurate (for example, recognising that the AI did not consider vision), others attributed the system with capabilities it did not have, such as incorporating regional referral policies.

9.3 Risk Aversion and Decision Confidence

A central factor shaping optometrists' interpretations of AI outputs was concern about clinical risk, particularly the fear of missing pathology that could result in harm to patients or have professional consequences. This perceived risk often encouraged a defensive approach to patient care, with participants describing a preference for caution in situations of uncertainty. As the following section explores, this risk-averse mindset influenced how AI outputs were interpreted and used, especially when probability values for different management options were presented. The interplay between clinical responsibility and uncertainty is therefore critical to understanding how AI-CDSS tools are received in practice.

Many participants described a reluctance to take risks when making management decisions, expressing concern about the consequences of missing pathology. This tendency often led them to adopt an overly cautious approach.

"You always worry about being caught out — it's easier to refer than to get it wrong." - ***Participant 17***

This cautious mindset also shaped interactions with the AI system, particularly when its outputs included multiple probabilities. For some, even a low probability of an urgent issue was enough to influence their decision-making.

"What if somebody asked me why I didn't refer urgently? Because the urgent is still 26%, which is a fair whack." - ***Participant 2***

The concern about risk was evident across both hypothetical and clinical contexts. Even when presented with example cases that carried no real-world implications, participants tended to adopt a cautious approach, particularly when uncertain about the diagnosis. For case 1, for example, half of the participants stated they would refer urgently or, if not referring, arrange a short-interval follow-up to confirm the accuracy of their assessment.

The AI's presentation of percentage probabilities for all management options was generally considered clear; however, it also introduced uncertainty for some. Several participants described feeling confused when a management option such as urgent referral appeared with a relatively low probability, despite being 'ranked' second after routine referral. This contributed to feelings of uncertainty and reinforced their preference for cautious management.

"Uh but having then that 6% of it thinks that it should be an urgent referral, I do not think it's great for a primary care optometrist in a busy clinic because we have to make quick decisions. And if it is saying that 6% of it thinks that it needs an urgent referral, that's just going to confuse me." - ***Participant 18***

"My questions would be around 6% for urgent referral. I, I'm just like, why? Like, what? Why? Because I, I'm struggling with the 90, the difference between 90 and a hundred percent, I guess. Are you with me? Like, why would it suggest 6% urgent referral?" - ***Participant 1***

In contrast, participants found the AI's presentation of diagnostic outputs for the three clinical cases (detected vs not detected) much easier to interpret. No concerns were raised about the absence of confidence values accompanying these outputs.

"I definitely think the grid with the ticks is a very easy and clear way to be presenting what there is" - ***Participant 6***

In clinical practice, the decision to refer, and the level of urgency assigned to that referral, is the key management judgement optometrists make, with significant implications for patient outcomes. By displaying percentage probabilities for all management options, the AI system naturally drew some participants towards more cautious management, even when the likelihood of an urgent issue was low. One participant reflected that this tension between statistical outputs and clinical realities reflects a broader divide between research and practice.

"I think this is a really good example of where research doesn't meet clinical very well. In research, yes, we'd look at stats, and we would never look at anything without stats." - ***Participant 1***

These risk-averse tendencies may also explain why participants preferred the simplified detected/not detected presentation for diagnostic outputs and did not express concern about the absence of confidence values in that context.

9.4 Preconceptions of AI

Before being introduced to the example AI system, participants were asked to reflect on their current knowledge of AI technologies developed for eyecare and to share their perspectives on the potential use of such systems in primary care. As noted, during this phase of the interview, several participants expressed optimism about AI's potential to enhance their practice, emphasising the perceived benefits of integrating AI. Conversely, some optometrists exhibited scepticism, acknowledging some positive aspects but predominantly focusing on concerns regarding AI's design and potential role. Despite these initial attitudes being based solely on speculation, they appeared to influence how participants interacted with the example AI system when it was later presented, regardless of whether its outputs agreed or disagreed with their initial assessment of the clinical cases.

9.4.1 Perceived Positive Aspects of AI

Participants reflected on several ways AI could offer meaningful benefits in optometric practice. While recognising its limitations, many highlighted potential advantages of AI tools when integrated thoughtfully into clinical workflows.

Enhanced Diagnostic Support

Some participants expressed their views that AI could be a beneficial tool for supporting their diagnosis and management decisions. One way this tool could be beneficial is through providing a second opinion, that supports the optometrist's interpretation and improves their confidence in their management.

"I think it'll be quite useful because even though I think we're getting better at reading OCT images, sometimes it's just nice just to know for sure and you don't have to sort of go back and forth and think do I need to refer? So, to know actually yeah that definitely is an exudate or that's a full thickness macular hole. I think it just gives you that guarantee really." - ***Participant 20***

AI could also highlight areas of concern that might not have been apparent to the practitioner during their assessment of the case. This was seen as particularly useful in complex cases where additional analysis could improve diagnostic accuracy.

Efficiency and Timesaving

AI was recognised by participants for its potential to improve efficiency in clinical practice. By automating certain aspects of the eye examination, AI could save time for optometrists when they are analysing OCT imaging, allowing them to prioritise other aspects of patient care.

"I understand that artificial intelligence is obviously designed to simplify things and give you a guide to make things quicker, faster. So, I'm totally for it." - ***Participant 19***

The potential time-saving benefits of AI were considered particularly valuable, as several optometrists described the challenges of working under significant time constraints during eye examinations. In busy clinical environments, limited appointment durations require clinicians to carefully balance thorough patient care with the need to conduct examinations efficiently, ensuring that critical clinical features are not missed.

Training Less Experienced Optometrists

Participants acknowledged that AI could be especially valuable for less experienced optometrists, offering guidance and reducing the likelihood of missing subtle abnormalities. In this way it could act as a training tool to guide these clinicians.

"It would definitely make a big difference, especially with anyone that's newly qualified or hasn't used OCT because I don't think even now the more recent graduated pre-regs, they have not much idea on OCT at the moment. [AI] would definitely help them in my opinion." - ***Participant 8***

9.4.2 Scepticism

Other participants were more sceptical of the introduction of AI into primary care practice and highlighted reasons for their scepticism. Their concerns centred around the limitations of AI in capturing the full complexity of patient care, its potential to diminish professional judgement, and broader implications for the role and identity of optometrists.

Lack of holistic assessment

The overwhelming view from participants was that if implemented in primary care, AI should be a tool that supports optometrists rather than replacing them for specific tasks. The main reason that optometrists expressed for this was that they believed AI would be unable to provide a holistic examination of the patient. This holistic assessment is deemed to be important and needs to include the consideration of results from other optometric tests, but also a personable element that AI would be unable to replicate.

"You cannot feed the patient's emotions and concerns. From the years I've been doing this, a lot of what I do is from what the patient tells me in the room and the feeling I get, you know, which is something you cannot teach my trainees yet because they're just so new and you cannot teach an AI machine that." - ***Participant 19***

"AI's never going to be a caring tool. We can see it in an elderly patient who doesn't have many years left and we know that's not necessarily something we'll write on our notes but putting that person through a glaucoma referral is just cruel sometimes […]. Or if your patient is frightened, I guess where AI is going to fall down is where

are you going to get the comms from? No one wants a robot telling them, okay, these are your chances." - ***Participant 1***

Over-Reliance

Another significant concern was the potential for over-reliance on AI. Participants worried that if AI systems became too integral, optometrists might begin to trust the technology blindly, potentially overlooking important clinical signs that AI might miss. This reduced professional vigilance and bias towards the AI outputs could lead to optometrists' clinical judgment being impacted.

"The problem you have there is that some may rely on the AI a bit too heavily. And it may cloud what they're actually seeing." - ***Participant 6***

"I think the worry about that is if someone was to have an OCT scan and then you let it analyse it and it says it's okay, and then people might not look at the scan and just say 'well the AI says it's fine so you're fine.'" - ***Participant 9***

Accuracy and Reliability

Concerns were raised about the accuracy and reliability of AI systems. Participants also expressed doubts about AI's ability to handle complex cases, particularly when there are multiple factors at play. Participants expressed worry that AI might miss or misinterpret subtle findings, leading to incorrect diagnoses.

"It depends how intelligent the AI is from my experience, just of the medical field and their use of AI, it can quite often not be a hundred percent correct, or you still need other information that the AI doesn't have on the patient to influence your decision." - ***Participant 6***

"It depends on the sensitivity, doesn't it? If it misses it and says, oh, we'll rescan that again, whenever, and by that point the patient's vision's gone [...]. I just wonder whether there is a limit to the AI's interpretation and knowing how ambiguous these scans can be. Until the accuracy of the scans improves to eliminate the ambiguity, whether AI would be successful... I'm not sure." - ***Participant 11***

Professional Implications

Ethical concerns were also mentioned, particularly regarding the potential for AI to erode the professional role of optometrists. Some participants expressed unease that increased reliance on AI could devalue the profession by creating the perception that machines can perform aspects of the role as effectively as clinicians. These concerns raised broader questions around job security and how the unique expertise of optometrists might be perceived in the future.

"I guess you are always going to have bias as an optometrist in this question, I think, because you're going to say, don't replace me." - ***Participant 10***

"Essentially this opens a debate as to whether it makes the optometrist redundant." - ***Participant 13***

Overall participants generally saw AI as a helpful tool that could enhance diagnostic accuracy, improve efficiency, and support less experienced practitioners. AI was valued for its potential to assist in decision-making and provide objective analysis. However, there were concerns about over-reliance on AI, the potential loss of clinical judgment and doubts about AI's accuracy. Participants emphasised the importance of AI being used as a supplementary tool rather than a replacement for human expertise.

9.5 Summary

This chapter has explored how optometrists perceive and interact with AI-enabled clinical decision support systems (AI-CDSS), with particular emphasis on usability, trust, and alignment with clinical practice. Through qualitative analysis of interviews and case-based demonstrations, it became evident that while segmentation maps were often appreciated for their interpretive clarity, management suggestions were met with scepticism due to their lack of context and perceived detachment from real-world variability.

Key factors shaping the acceptance and utility of AI-CDSS included optometrists' attitudes toward risk, their preconceptions about AI, and the extent to which AI outputs supported rather than supplanted clinical judgment. Risk aversion led to cautious decision-making that influenced how probabilistic outputs were interpreted, while both enthusiasm and scepticism toward AI strongly predicted user interaction patterns and trust.

These insights form a foundation for Chapter 10, which synthesises the findings from this and earlier chapters to discuss broader implications for practice, training, and the future design of AI in optometry.

Chapter 10: Discussion

This chapter revisits the key research questions outlined in Chapter 1.

Research Questions 1 and 2, which focus on optometrists' referral accuracy and the interventions implemented to reduce the number of false positive referrals being seen in the HES, were addressed in Chapters 2 and 3 through two systematic literature reviews. These chapters examined the evidence available at the time of completion of each review and discussed its relevance to the aims of this thesis. Since the completion of those reviews, additional studies have been published which are relevant. This discussion chapter therefore re-examines the research questions whilst considering any relevant and more recent literature that has been published since those systematic reviews were completed, assessing whether these new findings enrich the discussion or challenge any of the initial conclusions.

This chapter then revisits research questions 3 to 7. The AI-CDSS focused research questions are addressed through an integrated discussion of key considerations for the real-world adoption of AI-CDSS in primary care optometry practice, whilst drawing on optometrists' experiences with OCT imaging and their perspectives on AI as a supportive tool for decision-making. The findings from this research highlight not only the promise of AI but also the importance of aligning its design with the realities of clinical practice, to help optometrists in making more informed patient management decisions.

10.1 RQ1. How accurate are referrals from primary care optometrists, particularly in relation to retinal conditions?

This question was addressed through a quantitative systematic review that evaluated the accuracy of referrals originating from primary care optometric practice, with a particular focus on false-positive referrals (216).

Chapter 2 concluded that optometrists' referral accuracy is variable and often sub-optimal, especially for glaucoma, which accounts for a large proportion of HES workload in the UK. False-positive rates remain high, and while cautious referrals may reflect appropriate clinical judgement, they contribute to unnecessary hospital appointments. Chapter 2's review also highlighted a clear gap in the literature concerning optometric referrals for macular affecting conditions. Only one relevant study was identified at the time of the review, which was conducted in 2011 (28), prior to the widespread adoption of OCT imaging in primary care. While several studies have evaluated the general accuracy of optometrist referrals, few have provided sub-analyses specifically on retinal conditions, which this thesis mainly focused on. Since the completion of that review in 2022, two more recent UK-based studies have aimed to address this gap. One, although only available as an abstract, was presented at the ARVO 2024 conference and investigated the accuracy of referrals for wet AMD over a four-month period in 2023 (217). Of the 111 referrals assessed, only 52% were confirmed as wet AMD by secondary care. OCT was included in 66% of referrals, with an accuracy rate of 56%, compared to 45% accuracy in referrals without OCT. The findings suggest that the inclusion of OCT imaging may improve referral accuracy for wet AMD although further training in its interpretation remains essential.

A retrospective analysis of 394 referrals from primary care optometrists to a UK HES examined diagnostic accuracy across a range of retinal conditions (218) with referrals grouped into pre-COVID and COVID periods. Notably, wet AMD referrals, comprising the largest diagnostic group (n = 256), had the lowest diagnostic accuracy at 39.8%. OCT data were mentioned significantly more often during the COVID period, rising from 9.1% pre-COVID to 23.7%, possibly reflecting changes in consultation practices, increased device availability, or greater emphasis on reporting OCT findings.

Although the literature is still lacking for retinal condition referral accuracy, these two recent studies indicate that referral accuracy for retinal conditions, particularly wet AMD, remains relatively low. While the inclusion of OCT may improve accuracy slightly, it suggests that access to imaging alone is not sufficient for improving optometrists' referrals and further supports the idea that interventions such as AI-CDSS have potential to improve referral decisions. Some conditions, such as macular oedema and wet AMD continue to be more challenging, often due to overlapping features with dry AMD. This suggests the need for greater focus on these conditions in clinical education and support.

10.2 RQ2: What strategies have previously been used to reduce the number of false-positive referrals from optometrists to secondary care ophthalmology and have they been successful?

This question was initially explored in Chapter 3 through a second systematic review (219) that synthesised evidence on interventions and system-level approaches aimed at improving referral quality. During that review, referral filtering schemes for glaucoma and cataract were covered in detail. Since then, one study has assessed the implementation of a referral refinement scheme for wet AMD in Wales (220), whereby refinement of referrals was carried out by a specially trained community optometrist who assessed patients through history, examination, and OCT. Based on findings, the optometrist either referred for further assessment if neovascular AMD was suspected, discharged the patient, or monitored them. That study found 94% of new wet AMD cases received treatment within two weeks in the new pathway, compared to 85% referred using traditional referral routes, alongside a significant increase in confirmed diagnoses. The community optometry-led pathway showed clear benefits of faster treatment access and fewer false-positive referrals and therefore provides supporting evidence for an option of community refinement in retinal disease. However, it focused only on wet AMD and did not assess other retinal conditions.

As part of the original systematic review, it was also identified that there was a lack of published research into the acceptability of teleophthalmology referral pathways, and that a pilot was then taking place, the HERMES study, (126, 127) which used a cluster randomised trial to evaluate a teleophthalmology referral pathway for retinal disease, and included the assessment of the accuracy of an AI diagnostic support system for automated diagnosis and referral recommendation. One study by Patel et al. (221) reported specifically on the experiences from patients and clinicians (primary care optometrists and HES ophthalmologists) of the teleophthalmology aspect of that pathway via an interview study. Patients were largely positive about teleophthalmology, valuing faster referrals and fewer unnecessary hospital visits. However, some were concerned about not receiving updates on their referral outcome. Some also felt uneasy about not having face-to-face contact, missing the reassurance of speaking directly to a clinician. Clinicians welcomed teleophthalmology for improving efficiency, reducing hospital pressures, and enabling quicker triage. Optometrists appreciated receiving feedback from ophthalmologists, helping them refine future referrals. Still, concerns included the cost of equipment, lack of funding, time to complete referrals, and training needs, especially for smaller practices. Although just one study, these findings suggest overall support for teleophthalmology referral platforms from both patients and clinicians and support their implementation to improve referrals from primary to secondary care.

The potential use of artificial intelligence (AI) to improve the accuracy of referrals entering the HES was also not covered in the initial literature found as part of the literature review in Chapter 3, highlighting a discrepancy between the volume of research that was currently focusing on AI for aiding the diagnosis and management of ophthalmic conditions, and the research published specifically for this use case of optometry referrals. Three studies have since assessed the use of AI within a triaging pathway from primary to secondary eyecare. The first was used for referrals of all conditions, using a web-based CDSS developed using guidelines and expert input to generate a provisional diagnosis and urgency level (222). The CDSS outperformed referring providers in diagnostic accuracy and urgency assessment, showing stronger agreement with ophthalmologist evaluations and helped standardise data collection and streamline electronic referrals.

The other two studies focused specifically on retinal conditions, which are most relevant to the focus of this thesis. Liu and colleagues (153) implemented an AI-powered telemedicine platform using OCT imaging in primary care clinics in Shanghai to assess for retinal diseases and refer patients to a hospital if required. Among 1,257 participants, 394 had retinal issues, with 146 requiring urgent attention. The AI system showed high accuracy of over 96% sensitivity and specificity for identifying both urgent and routine cases. Although the study was implemented in a screening context, it demonstrates potential for referral refinement through its implementation for early detection and referral of retinal disease in real-world settings.

The last study relates again to the HERMES study, whereby the Moorfields-DeepMind AI system, as used in this thesis, was evaluated for its ability to support referral decisions based on OCT scans (223). While it showed high sensitivity for identifying cases needing referral, its low specificity led to frequent over-referral, especially for conditions like dry AMD that do not typically require hospital input. The AI's performance was similar to community optometrists but less accurate than hospital clinicians. Its reliance on imaging alone, without clinical context, likely contributed to its cautious approach. Additionally, compatibility issues meant the AI could only analyse just over half of submitted scans, currently limiting its real-world utility without further development. The relevance of these findings is discussed in later sections of this chapter, whilst comparing to the findings from the studies completed as part of this thesis.

Overall, the updated review findings demonstrate that research is being carried out in AI-CDSS for improving referral decisions in optometry, with mixed findings. There is still, however, a clear gap in the literature of human-computer interaction research in this area which part of this thesis aims to address.

10.3 RQ3: How do optometrists experience and use OCT imaging in their day-to-day clinical practice, particularly in the management of patients with suspected retinal disease?

This question was explored through a qualitative interview study that investigated how OCT findings are interpreted and incorporated into the optometric consultation process.

The interview findings in Chapter 7 highlighted clear patterns in how optometrists engage with OCT imaging, with approaches shaped by their years since qualification. Four participant profiles were identified: newly qualified optometrists (Type 1), OCT-integrated optometrists (Type 2), experienced optometrists who remained hesitant about OCT (Type 3), and experienced, early adopters (Type 4) who embraced the technology. These profiles illustrated a variety in confidence, usage of OCT and perceived value of OCT in practice. The following subsections explore three key discussion points from these profiles: the importance of early exposure and training, the role of professional identity and confidence when navigating uncertainty, and the influence of support structures and compatibility on technology adoption.

10.3.1 The importance of early exposure and training

Early exposure to OCT imaging plays a critical role in shaping long-term confidence and routine use among optometrists. Type 1 and Type 2 participants, who encountered OCT during university or soon after qualification, albeit to different degrees, demonstrated greater ease in integrating the technology into their clinical practice. In contrast, Type 3 participants, who qualified prior to the widespread adoption of OCT, frequently expressed uncertainty or reluctance, often citing the absence of structured training or support as a barrier to them being confident with its use. This contrast highlights the impact of foundational training on professional behaviour and confidence. As such, ensuring that OCT interpretation is embedded within undergraduate curricula and that post-qualification practitioners have access to formalised training may be essential for supporting effective adoption of advanced imaging technologies across the profession. As OCT is such a useful tool, and becoming more readily available, early exposure is essential.

10.3.2 The role of professional identity and confidence when navigating uncertainty

Differences in how optometrists respond to clinical uncertainty appeared to influence their use of OCT in meaningful ways. Newly qualified practitioners (Type 1) were generally more accepting of uncertainty, often viewing gaps in knowledge as part of the natural process of developing clinical expertise. They regularly sought second opinions and engaged in peer discussions, not only for reassurance but as opportunities for collaborative learning and skill-building. This aligns with work on new junior doctors' experiences when transitioning from medical student to the workplace (224) which highlighted how early-career clinicians often develop their diagnostic skills by recognising uncertainty, with a low threshold for seeking external advice in order to manage patients safely.

In contrast, more experienced optometrists in the Type 3 group expressed greater discomfort with diagnostic uncertainty, often linked to their fears of error and professional accountability. This occasionally led to defensive decision-making, such as referring more frequently to secondary care to minimise perceived risk. Similar patterns have been observed in other clinical settings. One study by Ilgen et al. (225) described how clinicians, when unsure how to safely proceed, often "hand over" care to colleagues with different expertise, using referral as both a clinical and emotional safety mechanism. A systematic review into primary care clinicians by Alam et al. (226) similarly found that diagnostic uncertainty can trigger emotional and cognitive stress, with fear of making mistakes contributing to increased use of investigations and referrals. In the interview study of this thesis, these pressures appeared to limit confidence in OCT interpretation, particularly among those without sufficient formal training, reinforcing the need to support experienced practitioners in managing uncertainty and building confidence with new technologies.

Professional identity also played a role. More experienced optometrists tended to feel that they were expected to “know already,” which discouraged them from admitting uncertainty or seeking support to update their clinical knowledge and practice. This pattern of behaviour aligns with Gabbay and le May’s concept of ‘mindlines’ (227), which is internalised knowledge built through repeated social interactions rather than formal guidelines. In the context of OCT use in primary care, more experienced practitioners may be less inclined to update embedded habits unless prompted by trusted peers or local consensus. This resistance to changing established practices may partly explain reluctance to engage with unfamiliar technologies like OCT, especially when formal training or structured feedback is lacking.

Together, this suggests that addressing uncertainty in optometric decision-making requires more than technical training. Supporting experienced practitioners to navigate uncertainty may help reduce unnecessary referrals and foster more confident, autonomous decision-making in OCT use.

10.3.3 The influence of support structures and compatibility on technology adoption.

While access to OCT is a prerequisite for its use, the interview findings in Chapter 7 demonstrated that access alone is insufficient to ensure effective adoption. Type 3 and Type 4 participants had similar levels of experience and access to OCT, yet their engagement with OCT in practice differed notably. Type 4 optometrists embraced OCT due to perceived clinical value and prior exposure in environments like the HES. In contrast, Type 3 participants found integrating OCT more difficult, citing complexity, lack of support, and perceived incompatibility with their examination style/routine. This distinction reflects key principles from Rogers’ Diffusion of Innovations Theory (228), particularly the roles of compatibility, trialability, and observable benefit in shaping adoption decisions.

These findings align with broader evidence from other areas of healthcare. For example, a systematic review (229) identified that adoption of health information technologies is influenced more by perceived usefulness, ease of use, and social and organisational support than by availability alone. Another review (230) found that physicians' uptake of electronic medical records was constrained by usability issues and workflow disruption, despite clear benefits. Together, these studies support the conclusion that structural access to technology must be accompanied by meaningful support and perceived relevance to ensure widespread clinical adoption.

10.3.4 Relevance to future AI adoption in optometry

The factors influencing OCT adoption among optometrists provide valuable insights into potential enablers and barriers for future AI implementation in optometry. As highlighted with OCT, access to AI tools alone is unlikely to ensure meaningful uptake. Successful adoption will depend on how well AI systems align with clinical needs and practitioners' clinical confidence. For example, Type 4 optometrists, who already feel proficient in interpreting OCT scans, may perceive limited relative advantage in adopting AI, particularly if they view such tools as unnecessary or poorly integrated into their workflows. In contrast, Type 3 practitioners, despite being hesitant adopters of OCT, were more receptive to AI with it positioned as a supportive tool that could help build confidence. Their lack of experience with OCT may create a stronger perceived need for diagnostic support, increasing the perceived usefulness of AI. According to Rogers' Diffusion of Innovations Theory (228), innovations are more likely to be adopted when they offer a clear relative advantage and are compatible with existing values and practices. These attributes may vary based on an optometrist's level of experience and comfort with diagnostic imaging.

10.4 RQ4: Where do optometrists currently seek information or support when faced with clinical uncertainty regarding OCT findings, and why are sources favoured?

Chapter 8 highlighted how optometrists use a range of different information sources to improve their OCT knowledge. These sources can include 'official' channels of information such as training courses or guidelines, or interpersonal sources depending on links with other healthcare professionals. Several previous studies have looked at other primary care clinicians' information sources and have identified similar information-seeking behaviours (227, 231, 232). Chapter 8 adds to this knowledge by identifying these sources specifically for primary care optometry, with a focus on OCT imaging.

10.4.1 Proactive and Reactive Learning

A novel contribution of the findings outlined in Chapter 8 is the distinction between optometrists' proactive and reactive learning for OCT interpretation. A significant amount of previous literature has focused on what this thesis describes as 'reactive' learning, i.e., when clinicians seek information as they encounter clinical uncertainty. Studies have covered the approaches taken by clinicians in detail (233) and overall, like Chapter 8's findings, emphasise the importance of time sensitivity and evidence of credibility/accuracy (227, 231, 232).

In comparison, there is less information in the literature about how healthcare clinicians seek information in preparation for a specific clinical encounter or finding, as highlighted in the interview findings in Chapter 8. One ethnographic study by Gabbay and le May (227) discussed how nurses would look at clinical guidelines in preparation for a meeting or to ensure that their own practice was up to date, and once they were familiar with a procedure would not look at the guideline again. A review also indicated how nurses should be well informed of research findings to ensure that they practice according to current guidelines (233); however, in neither of these studies was this framed as being proactive and was not clearly distinguished from reactive behaviours. One study by Lai et al. (234) looked at 'proactive' behaviours in healthcare workers where the authors describe approaches such as using personal initiative and problem-focused coping for anticipated problems. They present an example of using active problem solving through a voluntary expenditure of effort to eliminate problems and improve performance; however, they did not describe these behaviours in relation to how they shape clinical information seeking.

Chapter 8 also provides a novel application and integration of Kolb's Experiential Learning Theory and Schön's Reflective Practice Model to explain how optometrists make sense of new information during proactive and reactive information-seeking in OCT interpretation. By adapting these models for optometric practice, the thesis provides a conceptual framework that captures the dynamic, cyclical nature of learning and decision-making in primary care optometry. The dual-model approach contributes to knowledge through a deepened understanding of how optometrists build expertise through iterative, experience-driven processes.

10.4.2 Trust Built on Evidence: How Optometrists Evaluate Information Sources

The interview study findings in Chapter 8 highlight how optometrists' trust in information sources is strongly rooted in the perceived credibility and accuracy of those sources, often using their own methods of validation through experience. As discussed, in current practice, optometrists often rely on evidence-backed resources such as clinical management guidelines from the College of Optometrists to provide proactive information for clinical management. This reliance on experience-validated information sources is consistent with broader healthcare research, where clinicians use information that is not only authoritative but also validated through repeated clinical use (231, 232). In the specific context of OCT training, proactive learning can also often take the form of validated resources such as university-provided further training and qualifications. These 'official' resources are often trusted by clinicians as they feel they have been externally verified.

Ophthalmologist consultants were often automatically seen as a reliable source of information due to the perceived hierarchy of consultants based on their more advanced ophthalmological training. Colleagues and peer networks also play a critical role; however, optometrists are only willing to rely on peers when they have confidence in their peers' expertise and background, effectively treating these factors as indirect evidence that they are reliable. The extent to which a peer is considered trustworthy can depend on their clinician setting (i.e., whether they have HES experience or not) but was mainly based on prior experience working or studying with them. This emphasis on trust filtered through personal experience echoes Gabbay and le May's ethnographic findings (227) among primary care clinicians, who found that practitioners turned to selectively trusted professional networks whose judgement had proven reliable over time. Their findings, along with those in Chapter 8 reinforce the idea that trust in peer-derived information is more about situated judgement and experience.

These perspectives illustrate that while peer consultation is a valuable information source, optometrists carefully assess the credibility of the colleague before seeking advice. Rather than relying on general peer networks, they prioritise those with proven knowledge to ensure that the information they receive is both trustworthy and clinically relevant.

10.5 RQ5. How do optometrists' diagnostic decisions and trust in AI-CDSS change when exposed to ambiguous or incorrect AI outputs, and what is the impact of different presentation formats such as segmentation overlays? AND RQ6. How should outputs from an AI-CDSS be designed to ensure they are clinically useful for optometrists?

This subsection addresses research questions 5 and 6 by discussing how both the interview study findings, covered in Chapters 7-9, and the quantitative study findings, covered in Chapter 5, may inform the design and presentation of an AI-CDSS in primary care optometric practice.

10.5.1 Quantitative Findings

Research question 5 was the focus of Chapter 5, where quantitative data from a previous study was reanalysed to gain new insights and further understanding into how optometrists' diagnostic decisions and trust are affected when exposed to ambiguous or incorrect outputs from an AI-CDSS. The study deliberately included cases where the AI output either disagreed with the reference standard or presented clinical ambiguity, thereby simulating real-world uncertainty. The findings showed that diagnostic accuracy declined when AI suggestions, especially those accompanied by segmentation overlays, were introduced. Although segmentation overlays increased participants' trust in the AI, they often led to overinterpretation of subtle or clinically insignificant features, resulting in reduced diagnostic accuracy. This effect was seen regardless of experience level, suggesting that while segmentation maps may enhance perceived transparency, they can also mislead users when not closely aligned with clinically significant findings. These results highlight the importance of aligning AI visual outputs with clinical relevance and the need for thoughtful design in presenting AI information to clinicians.

As with Research Questions 1 and 2, the discussion of these quantitative findings, and their relationship to existing literature, was initially developed earlier in the PhD programme. However, more recent literature searches have identified additional relevant studies that build upon and further contextualise these results, offering deeper insights into the research question.

One study by Goh et al. (177) found that physicians were influenced to modify clinical decisions in chest pain triaging based on GPT-4 assistance, and that this improved accuracy scores. Another study compared three AI-CDSS protypes with forms of explainability to a validated scoring system for strep throat prediction in telehealth screening using a randomised experiment. That study reported that AI-CDSS improved clinicians' predictions compared to the traditional scoring, with higher agreement with AI. However, participants reported lower trust in AI advice, with more requests for in-person testing (235).

A third study was most similar to the study outlined in Chapter 5 and examined how varying levels of explainability in AI-based CDSS influence clinicians' trust and diagnostic performance in breast cancer detection (236). The authors designed the experiment to expose participants to decision support with an increasing level of explanations. That study found that although AI support overall improved diagnostic accuracy, the two types of AI support with the most detailed explanations showed significant reductions in diagnostic accuracy, like the quantitative findings in Chapter 5. In contrast to Chapter 5's findings, the breast cancer study reported that an increase in the level of AI explainability did not enhance the level of reported trust in the AI system. Interestingly, the authors also reported that the more detailed information led to a lower perception of AI accuracy. Although derived from different medical domains and involving distinct clinical case selections, these additional results, when considered alongside the earlier discussion in Chapter 5, underscore the diverse impacts, both beneficial and detrimental, that AI-generated explanations can have on clinical decision-making. These findings highlight the critical importance of exercising caution when incorporating explanatory features into AI-CDSS, given the potential for unintended adverse consequences.

10.5.2 Optometrists' Preconceptions of AI

The perceived benefits and concerns shared by participants in relation to AI-CDSS broadly reflect themes that are already well-documented across the wider AI in healthcare literature (237). Optimism about improved diagnostic support, time efficiency, and support for less experienced clinicians have been widely reported (237, 238), as have concerns about over-reliance, loss of clinical autonomy, and AI's inability to accommodate holistic aspects of patient care (237, 239). However, what distinguishes the findings from the interview study is the specific application of AI to support OCT interpretation in primary care optometry, a setting where, as highlighted in Chapters 7 and 8, the imaging technology itself is still relatively new, and its integration into routine practice remains uneven. Previous studies have explored optometrists' views towards AI in practice generally (186), and specifically for diagnosing retinal disease (240). However, these two studies used surveys and therefore did not acquire as rich a perspective as was gained during the interview study in this thesis. A third study used semi-structured interviews with optometrists; however, this was mainly to discuss expectations and concerns about contributing digital retinal images to form an extensive research repository that also uses AI-CDSS, non-specific to OCT imaging (241).

The context in this thesis shapes how optometrists perceive the usefulness and risks of AI-CDSS outputs, offering valuable insights into how such systems should be designed and introduced. It highlights how AI is being evaluated not just on its general potential, but in relation to a relatively complex clinical task that some practitioners do not yet feel fully confident in managing. This situates the findings as a contribution to understanding AI implementation in emerging diagnostic domains, where the interaction between human and technology is still being negotiated.

Perceived Benefits

Participants expressed enthusiasm about the potential of AI to support their diagnostic reasoning, particularly by offering a second opinion in borderline or ambiguous OCT cases. This aligns with widely recognised benefits of AI in enhancing clinician confidence and reducing uncertainty. However, within the context of OCT, where interpreting subtle features remains a developing skill for many optometrists, this perceived benefit is especially pronounced. Some participants saw AI as a reassuring tool to help confirm their judgement. This perception of AI as a supportive aid suggests that AI-CDSS outputs may be considered most clinically useful when they are seen as strengthening, rather than replacing, the optometrist's interpretive process; this matches the findings from the surveys by Scanzera et at (186), who reported a consensus that AI tools could augment optometrists' skills.

Efficiency gains were also seen as a major advantage. In line with broader healthcare literature (237), optometrists valued the potential of AI to streamline clinical decision-making and reduce time spent scrutinising complex scans. Given the time pressures reported in the interview studies, experienced in many primary care clinics, the perceived usefulness of AI is tied not only to diagnostic performance but also to its ability to integrate into existing workflows without adding friction. OCT imaging itself was being used by some optometrists as an additional source of information that was even ‘avoided’ (**Participant 2**) if the optometrist could help it. This means that any AI support should add as little further disruption as possible.

Another familiar theme in AI implementation is its potential role in supporting less experienced clinicians (239). This theme was particularly salient in the context of OCT, which many participants viewed as inadequately covered in undergraduate or early career training. Here, AI was imagined to potentially help bridge knowledge gaps and increasing accuracy in clinicians who may still be developing confidence in interpreting retinal scans. These findings reinforce that while perceived benefits of AI-CDSS are not new, their relevance is shaped by the maturity of the clinical task at hand.

Scepticism

Participants also voiced concerns that are well-recognised in literature on clinician trust in AI, including over-reliance on automated outputs, concerns about accuracy and reliability and professional implications if incorrect decisions are made based on AI suggestions. These concerns gain additional nuance in the context of OCT, where clinicians already report varying levels of confidence and expertise. Some participants worried that optometrists might be vulnerable to over-trusting AI outputs, particularly when facing unfamiliar cases. Such over-reliance on AI guidance could inadvertently encourage disengagement from the underlying scan data, a particularly risky prospect when the modality itself still requires active learning and interpretation.

The question of how AI outputs are interpreted is therefore closely linked to clinician familiarity with the domain the AI is intended to support. While automation bias is a general risk across clinical AI (242, 243), it may be more acute in emerging areas like OCT, where clinicians may not yet feel confident in contesting or verifying AI-generated findings. This vulnerability to automation bias in less familiar domains suggests a different kind of dynamic compared to well-established diagnostic domains, where there is an element of novelty in both the tool and the task which may compound reliance.

Concerns about holistic care also featured prominently. Participants repeatedly emphasised that AI would be unable to capture the broader clinical and emotional context that informs many of their decisions. While such concerns are common across healthcare settings (237, 239), they carry particular weight in optometry where, as outlined in ‘7.3 Complexity of Management Decisions in Primary Care’, decisions on whether to refer patients can involve complex judgements about patient wellbeing or other personal factors unlikely to be captured by an automated algorithm. These concerns indicate that even where AI-CDSS outputs are accurate, their usefulness and interpretation remain bounded by what the technology can and cannot account for.

Finally, fears about the potential erosion of professional roles were voiced by several participants, echoing widespread ethical concerns about the implications of automation for clinical identity. Such anxieties are likely to shape how AI outputs are received, especially if practitioners feel the system undermines their judgement or substitutes their role rather than enhancing it.

10.5.3 Elements of the AI-CDSS

Segmentation maps and Explainability

One aspect of the AI system that had a positive reception was segmentation maps. These were considered a useful way to help users interpret anatomical and pathological OCT features in a simplified way. This supports findings from a qualitative evaluation of the segmentation accuracy of the example AI-CDSS, by specialist clinicians, which reported good clinical applicability for both care management and research (158). The interpretation of specific OCT features, such as determining whether an area is fluid in the retina or not, can be made in isolation. Segmentation maps, in this regard, serve as foundational elements aiding optometrists in their comprehensive patient assessments. These maps offer the advantage of identifying such features more independently from external influences and focused clinicians’ attention on possible pathological features without making specific recommendations.

Due to their method of design, segmentations are an intermediate step which more closely mimics human assessment of OCT imaging components before considering what those components could be indicating. While the overall feedback for segmentation maps was positive, there were instances of participants expressing negative sentiments when the maps did not address their information needs such as failing to segment a specific area of interest. These instances of mismatch between user expectations and segmentation outputs highlight an important consideration for AI design with respect to the system's thresholds for outputs. The work in Chapter 5 highlighted the different thresholds for pathology detection that can exist during the AI training stage, i.e., detectable versus clinically significant and how human input in the training stage can create these. For the example AI system, the algorithm producing the segmentation maps was trained on thousands of manually segmented OCT images where subjective differences would almost certainly be present.

Enquiries may vary based on the individual's requirements from the support system but may also be task dependent. Tschandl et al. (2) noted that in skin lesion assessment, clinicians exhibit varying requirements based on the nature of their clinical question. For example, a clinician querying malignancy will have different information needs to someone considering a diagnosis from a range of different multi-class possibilities. AI support systems which could offer adaptability may therefore be of increased use in a range of clinical settings. Modifying segmentation maps may also allow users to interact with the outputs and indicate specific features/areas of the OCT that the user is unsure of or selecting a specific feature from a list of features that the clinician would like the AI system to 'search for'.

In the context of OCT interpretation, segmentation maps provide a useful interpretive aid that may enhance clinicians' trust in AI decision support systems. Although such maps do not reveal the underlying algorithms or model logic that drive AI outputs, they can highlight the specific retinal structures or regions the system has identified as relevant to its diagnostic or management suggestions. In doing so, they serve as an intermediate step, bridging the gap between opaque model reasoning and the clinician's need for visual validation. Rather than functioning as true explainability tools that open the AI's internal processes to scrutiny, segmentation maps support a form of interpretability, helping clinicians to follow the AI's attention and potentially reinforcing their confidence in the system's outputs.

As outlined in Chapter 5, the presence of segmentation maps significantly increased participants' trust in the AI, even when the accuracy of outputs remained unchanged between conditions. This suggests that visual interpretability, particularly when aligned with familiar clinical reasoning processes, may shape perceptions of transparency and trustworthiness more than accuracy alone. Explainability and interpretability in clinical AI remains a challenging goal. A number of systematic reviews have identified a lack of user-centred explainable AI systems in practice and noted that many tools still operate as ‘black boxes’, offering little in the way of rationale that can be understood or interrogated by end users (188, 189).

While segmentation maps do not offer insight into the AI’s internal reasoning, they do provide a visual cue that helped optometrists understand what the system was “looking at” and allowed them to compare this with their own interpretation of the scan. In the domain of OCT, where visual pattern recognition is a key component of clinical decision-making, this form of alignment between the AI’s focus and the clinician’s expertise may be particularly valuable. That said, caution remains necessary. Interpretability tools like segmentation overlays can foster a sense of transparency without necessarily offering meaningful insight into how or why a particular diagnostic or management suggestion was made.

Diagnostic and Management Suggestions

The interview study raised important considerations about whether AI-generated diagnostic and management suggestions should be presented to optometrists and under what circumstances they might add clinical value. While participants expressed a general openness to AI tools that support the interpretation of OCT scans, there was significantly more caution when it came to showing AI-generated outputs that indicate a retinal diagnosis or patient management suggestion, mainly due to these outputs being produced without access to wider clinical context.

Some optometrists did express support for the diagnostic suggestions, for the example clinical cases, especially when participants viewed the AI as offering a second opinion that helped confirm their own assessment of ambiguous OCT features. However, participants were clear that any diagnostic suggestion derived from an OCT image alone could not be considered definitive. Management suggestions, in contrast, were met with notable scepticism. Although optometrists frequently seek advice on patient management in practice, especially around referrals (Chapter 8), most agreed that recommendations based solely on OCT data lacked the necessary context to be useful. As outlined in Chapter 7, management decisions are influenced by a complex mix of clinical, personal, and systemic factors, including symptoms, case history, previous scans, and regional referral practices. This variability meant that AI-generated management suggestions were often seen as too generic and disconnected from the realities of practice. Several participants went as far as to suggest that management recommendations should not be shown at all, given the potential for confusion or misalignment with locally accepted pathways. The results from the interviews with optometrists by Constantin et al (241) support this view. In that study, there was a strong feeling from optometrists that clinical decisions must remain their responsibility, and they should have control. They felt that decisions should be based on all observations and not just what the technology is presenting.

The concerns around AI management suggestions are further supported by the findings of the HERMES randomised controlled trial (223), which evaluated the same AI system used in this interview study. In the HERMES trial, the Moorfields-DeepMind AI tool showed strong performance in identifying cases requiring referral, with high sensitivity. However, it also flagged a substantial number of cases unnecessarily, due to low specificity. This tendency to over-refer resulted in an overall performance that was similar to that of community optometrists but not as accurate as hospital-based clinicians. The AI's reliance on rigid rules and its inability to access broader clinical information were identified as likely contributors to this over-referral pattern. The HERMES findings (223) reinforce what participants in the interview study described. Diagnostic and management assistance may offer value when clearly positioned as a supportive tool, but standalone management suggestions were seen as insufficient and at times were considered misleading.

10.5.4 The influence of risk taking

The findings in relation to the effect of the level of risk associated with a task on optometrists' interpretations of AI outputs have possible design implications for AI-CDSS across a range of medical applications. Healthcare poses a unique environment where clinicians are often delegated to make choices and navigate risks associated with others. Providing explicit probability information improves decisions in low risk tasks (244). However, with decision-making that involves risk-taking, the way in which information, including decision support, is 'framed' is important to consider. Framing refers to how the presentation of information can influence decision-making; Newell et al. (245) discuss framing effects in the context of risk and uncertainty (245). In the use case, the AI's management suggestions were framed by presenting all four management outputs and their 'probabilities'. In comparison, framing AI diagnostic outputs as binary 'detected' or 'not' suggestions prompted a simplified interpretation of results by users which was received positively by the participants, perhaps due to the level of 'risks', i.e., the AI's probabilistic outputs for other, more urgent conditions, not being fully exposed. This contrasts with non-clinical applications of AI support such as bird classification, where a frequently expressed need from users was for the AI to display its confidence to better determine when to trust the AI's output (199).

Other research specifically into emotion or 'affect-charged' decisions such as medical management, suggests that due to associated risks, people systematically choose the optimal option less often (246). Others have suggested that the impact of probability information may therefore be attenuated in affect-rich choices (247), and people often rely on heuristic processes that compare outcomes between options while disregarding probabilities. Some of the participants were concerned about the risks of not choosing a more cautious approach when presented with AI management suggestions, despite the AI probabilistic suggestions favouring the less-urgent option. When designing AI systems for clinical applications there needs to be a balance between presented outputs not being misleading, in relation to what the AI is predicting, but also not encouraging suboptimal risk-averse behaviours.

10.5.5 Research vs practice

In the context of AI-assisted decision-making, behaviour is commonly characterised as occurring at a singular moment in time (such as during a medical consultation) and as encompassing a restricted set of choices (such as either endorsing or opposing a proposed diagnosis) (192). This framing of clinician behaviour is perhaps due to most of the research around these systems taking place in an academic community where the 'performance' of models is evaluated in a way that is disconnected from application (157). As highlighted during participants' evaluation of sample clinical cases and their perspectives on AI-driven management recommendations, making decisions regarding patient diagnosis and particularly management entails the deliberation of several interconnected factors. Systems taking these factors into account could enhance the diagnostic precision of the algorithm. For example, patient-centred questions such as 'is he a welder?' or 'does he have a high-pressure job?' may hold varying importance to different clinicians when making clinical decisions.

The 'gap' between AI designed for research vs clinical application is also apparent when systems are optimised for specific tasks or conditions. Bach et al. (167) reported that an AI system for diabetic retinopathy was considered deceiving, as the image analysis focused solely on diabetic retinopathy, thereby excluding other eye conditions that may be present. Although the example AI system was designed to detect several different types of retinal pathologies, its accuracy was (purposely) biased towards more urgent conditions. Much AI for healthcare currently stems from the forefront of AI research, where the primary intention is often to explore and demonstrate the feasibility of a novel AI model or algorithm (248, 249). Novel AI models are trained on clinical decisions made by doctors and are generally validated against the same type of data: in other words, their accuracy is compared to that of humans, and success is often defined as performing at or above human level. This type of comparison serves as a benchmark for evaluating the capabilities of the AI system as humans are considered the 'gold standard' in many clinical tasks. Therefore, comparing AI to human performance helps researchers and practitioners understand how well AI systems are performing, and demonstrating that AI can perform at or near human levels can help build trust and increase acceptance among stakeholders. However, the implication, then, (perhaps implicitly) is that AI systems tend to be conceived as replacements for humans. In contrast, it is generally accepted that in a health context, AI should augment rather than replace humans (250). Indeed, in the interviews clinicians indicated that they would like the AI to provide complementary information to help them take the decision. Furthermore, they indicated that AI segmentations, which supported them to interpret the OCT findings, were more helpful than management suggestions which present as a replacement to optometrists' holistic judgement. These findings call for closer collaboration between the HCI and AI communities around medical AI, to ensure that systems adequately meet clinicians' needs for real-world use (166).

10.5.6 Design Recommendations for Human-Centred AI-CDSS

The findings from the studies in this thesis emphasise that successful integration of AI-CDSS into primary care optometry hinges not only on technical performance, but also on alignment with clinical workflows, trust, transparency, and meaningful utility to clinicians. Based on optometrists' feedback and behavioural responses during interactions with the example AI system, several human-centred design recommendations can be proposed.

Support, Not Replacement

AI-CDSS tools should be designed to assist, not override, clinical judgement. Participants repeatedly stressed that they wanted systems that reinforced their autonomy and decision-making skills, rather than automated systems that dictated outcomes. Segmentation maps were generally welcomed as a form of visual support that enhanced interpretation, but full diagnostic or management suggestions were met with scepticism when they did not allow room for professional discretion. Preserving professional discretion is especially important in complex or ambiguous cases, where optometrists are weighing multiple factors beyond imaging. The design of AI-CDSS should therefore focus on augmenting rather than replacing the clinician's role, helping optometrists to feel empowered rather than undermined.

Tailored and Interactive Outputs

Information needs are not universal; they vary depending on the clinician's experience, familiarity with OCT interpretation, and the specific case at hand. Some participants reported needing help with identifying subtle features, while others sought support for confirming diagnoses or management decisions. Providing interactive features that allow clinicians to tailor AI outputs to their needs, such as selecting which overlays to view, magnifying specific areas, or toggling between different interpretation layers, can increase the utility and flexibility of AI-CDSS. This could be especially useful in a training context or when the clinician is managing cases outside their typical area of confidence.

Clarity Over Complexity

Participants expressed difficulty interpreting outputs that included multiple overlapping probabilities or nuanced suggestions for urgency. Many preferred straightforward outputs, especially in high-pressure settings where cognitive load is already high. Therefore, systems should prioritise clarity and reduce cognitive burden. Design strategies to achieve this could involve presenting results in a binary form (e.g., "refer" vs. "monitor") or using visual cues such as traffic-light systems or confidence bars. These simplified representations of AI output may be more digestible and usable in the time-constrained environment of primary care.

Explainability and Transparency

Trust in AI systems is closely tied to users' understanding of how they work. Several participants indicated they would have felt more confident in using the AI outputs if they understood how the suggestions were generated. Embedding segmentation overlays or summaries of the algorithm's reasoning, can help bridge the gap between opaque algorithms and clinical logic. Transparency is particularly important in edge cases or when AI recommendations contradict the optometrist's own judgment. This increased transparency also supports learning: newer or less experienced optometrists may benefit from being able to 'see' how the AI came to a certain conclusion, which may simultaneously act as a second opinion and an educational tool.

Regional and Contextual Adaptation

Management decisions in optometry are influenced not just by clinical findings but by local referral protocols, informal communication channels with secondary care, and variable access to resources. Participants described inconsistent or even conflicting guidance from local hospitals versus national bodies like the College of Optometrists. Given this variability, management recommendations from AI-CDSS must be adaptable to regional or practice-specific guidelines. Such over-reliance on AI guidance could be facilitated by allowing practices to 'localise' the AI system settings or choose from different management pathways based on their referral arrangements. Without such adaptability, AI suggestions for management risk being dismissed, as participants in this study frequently reported doing when recommendations were perceived as out of sync with their usual referral processes.

These five areas form the basis for the development of AI-CDSS tools that are truly usable and useful in clinical optometric settings. They represent a shift from a purely technical design approach to one that embeds the real-world complexity and human judgement central to effective and trusted AI practice in primary care optometry.

10.6 RQ7. At what point in the optometric consultation should an AI-CDSS for OCT interpretation be introduced to align with clinical workflows?

The integration of OCT imaging into optometric workflows varies considerably across practitioners, with implications for how AI-CDSS should be implemented. As detailed in Chapter 7, some optometrists described OCT as an integral part of the consultation, embedded early in the patient journey, often as the first step before history-taking or refraction. In these cases, OCT was not viewed as an “add-on” but as a routine tool that shaped the clinical routine from the outset. In contrast, others treated OCT as an additional or confirmatory investigation, used selectively after other tests had indicated potential concern.

Where OCT is positioned early in the consultation, AI-generated outputs would also be delivered early. A critical aspect to consider when designing AI-CDSS is the policies and sequencing of the system within decision-making workflows. Presenting AI outputs early would mean that there is potential to bias the clinician’s own assessment. Several participants expressed concerns that receiving AI suggestions too soon, particularly those relating to diagnosis or urgency, could introduce bias whereby the clinician’s independent judgement may become overly influenced by the AI’s initial interpretation. These concerns were supported in findings from the quantitative study in Chapter 5, where optometrists were presented with an example AI-CDSS alongside the OCT imaging and performed worse using the AI support for ambiguous cases, likely due to the influence of the AI support on their decisions. One published study (251) explored the influence of providing AI support at the start of a diagnostic session in radiology versus after and found that the participants providing responses prior to seeing the AI interface were less likely to agree with the AI, regardless of whether it was correct or not. They were also less likely to seek a second opinion from a colleague in cases of disagreement.

10.7 Interview Study Limitations

The following limitations relate specifically to the interview study. Limitations of the other studies within this thesis have been addressed in their respective chapters and so are not repeated. There are several limitations to the interview study. First, the focus was on a specific case study which means that it may not necessarily be representative of the clinical use cases of AI-CDSS in optometry/ophthalmology more generally. However, due to the complex decision making in clinical practice across a range of specialities, clinical cases tend to be specific, and the example highlighted key considerations.

Although the aim was to recruit participants with a range of experience in relation to OCT image interpretation, due to the method of recruitment requiring participants to volunteer, there was likely a bias in the participant group towards optometrists that are more confident in their ability to interpret OCT scans compared to the general population of primary care optometrists due to self-selection bias. The primary care optometrists who volunteered to take part therefore may not be representative of the broader population of UK-based primary care optometrists. Participants who chose to engage with a study focusing on OCT and AI are likely to be more professionally curious, more engaged with clinical development, and more open to or optimistic about emerging technologies. For example, as discussed in Chapter 8, professional curiosity was a theme among interviewees, but this may reflect the predispositions of those who chose to take part rather than a universal trait among primary care optometrists. Those with less interest, confidence, or engagement in OCT and/or AI may have been underrepresented. This could result in an overly positive portrayal of attitudes toward OCT and AI adoption and may limit the transferability of findings to the wider profession.

The choice was made to present one example AI system to optometrists with outputs presented in a specific way. This decision was made based on findings from the previous study outlined in Chapter 5 and discussions with the AI developers. Future studies into participants' deeper reflections into AI-CDSS design would provide a better understanding into how best to present AI outputs in this context. Ambiguous clinical cases were chosen as although this reduces ecological validity by not reflecting a natural mix of cases that would typically be seen in primary care, the focus was on interesting cases where clinicians may not be confident in their assessment, and how AI support would be interacted with in such cases. Finally, as previously emphasised, the best way to gain insights into AI-CDSS for clinicians is to implement them into real world practice. As the assessment was on the most appropriate method to display information to clinicians and the study aimed to gather views from a diverse group of optometrists practicing in different regions in England and Wales, it was not appropriate to test the implementation of an AI system into clinical practice at this stage. Despite the study being carried out online with example cases, the findings still found examples of barriers associated with implementing an AI-CDSS into practice.

10.8 Future Work

There are several avenues for future research that could build upon and extend the work presented in this thesis. Many of these opportunities arise directly from the methodological and contextual constraints of the interview study and quantitative study (Chapter 5) and addressing them would provide a more comprehensive understanding of how AI-CDSS can be integrated into primary care optometry. A priority would be the design of AI outputs for clinical use. This thesis demonstrated that participants' interpretations were shaped not only by what the AI suggested, but also by how suggestions were displayed. Because the interview study presented only one example system in a fixed output format, it remains unclear what design features are most effective for supporting accurate decision-making without being misleading. Future research should therefore investigate alternative presentation formats, ideally through co-design approaches with practising optometrists. Co-design approaches would enable practitioners to help shape the form, granularity, and framing of AI outputs.

Second, future research should focus on the evaluation of AI-CDSS in real-world clinical settings. Implementing AI-CDSS within routine primary care would allow investigation of how optometrists interact with outputs during consultations, where multiple factors such as time pressures, patient expectations, and availability of additional clinical information all have an impact. Such studies would provide a more accurate picture of how AI influences clinical reasoning across the full mix of cases seen in practice, not only the ambiguous examples considered in the interview study.

A further area that could be improved with further work is the diversity and representativeness of participants. Future research should include a broader range of clinicians, including those with less OCT experience and those less engaged with AI, to capture a fuller spectrum of attitudes and challenges. Longitudinal studies could also explore how exposure to AI over time influences confidence, reliance, and clinical judgement.

Finally, future research could build on both the interview and quantitative studies by exploring clinical decision-making processes in more depth. For example, observational studies or detailed exit interviews could provide insight into how clinicians integrate AI outputs with other sources of information during examinations. In addition, expanding case material to include a wider range of conditions, and providing richer patient information alongside OCT scans, would increase ecological validity.

In summary, future work should focus on two complementary goals: optimising the design of AI outputs and evaluating their use in real-world practice across a wider mix of clinicians and clinical scenarios. Together, these directions would provide the robust evidence base needed to ensure that AI systems are optimally designed to support decision-making in primary care optometry.

10.9 Conclusions

This thesis has explored how primary care optometrists engage with OCT imaging and examined the potential role of AI-CDSS in supporting diagnostic and referral decisions. Drawing on a mixed-methods approach, it has considered referral accuracy, current strategies for reducing false positive referrals, and optometrists' views and experiences of using OCT and AI technologies in everyday practice.

The findings underline the complexity involved in managing patients in primary care. While OCT is widely valued, interpreting its outputs can be challenging, particularly in cases that are not clear-cut. Clinical decision making was found to be influenced not only by the scan itself, but also by the patient's symptoms, history, social context, and the wider environment in which the optometrist is working. These factors created considerable variation in how the same clinical findings were understood and managed.

Attitudes towards AI support were cautiously positive. Many participants saw potential for AI to assist with the interpretation of specific features on OCT scans, particularly when offering a second opinion. However, diagnostic or management suggestions based solely on the image were generally viewed as insufficient, especially when they did not consider the wider clinical picture. Management recommendations in particular were seen as problematic, with several participants suggesting that they should not be displayed at all.

One notable finding was the perceived value of segmentation maps. Although not a direct explanation of the AI's inner workings, segmentation overlays helped participants understand what the system was identifying and why. This improved transparency and alignment with clinicians' interpretive practices appeared to build confidence in the AI's outputs, even though the underlying accuracy remained the same. The segmentation maps aligned with the way optometrists typically interpret OCT images, and in doing so, contributed to a greater sense of interpretability and trust.

Overall, this work examines, in detail, the differences in how optometrists have integrated OCT imaging into their practice and how their professional background significantly affects its integration and use. It shows that while AI tools can offer useful support for interpreting OCT outputs, systems must be carefully designed to reflect the complexity of clinical decision making, support rather than replace professional judgement, and foster trust without encouraging over-reliance.

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Appendices

Appendix 1: Mixed Methods Review Supplementary Tables

Author(s)	Year	Location	Study Period	Study Design	Aim	Condition(s)	Intervention	Main Results
Cottrell et al.	2022	UK (Wales)	April 2020-June 2020	Online Survey	To describe optometrists' independent prescribing (IP) practices during the COVID-19 pandemic in Wales.	All ocular conditions	Independent prescribing training and qualification	81 practices conducted 22,434 interactions. 80.26% were self-referred. **Prescriptions:** 1435 medications were prescribed, of which 1332 (92.82%) were topical. 1136 (79.16%) of prescriptions were issued in health boards with IPOS services, 288 (20.07%) in health boards with prescribers but no IPOS and 11 (0.77%) in areas with no prescribers. **Patient outcomes**: 2071 (9.23%) appointments ended in a referral to ophthalmology, 1300 (5.79%) to GPs, 1251 (5.58%) to pharmacies and 307(1.37%) to other professionals. Health boards with IPOS had fewest total and urgent referrals to ophthalmology. Health boards with no prescribing saw the highest proportion of referrals for urgent ophthalmology assessment. Significant association between the prescribing group and referral rates for urgent ophthalmology referrals ($p < 0.001$), and referrals to GP ($p= 0.001$), with a higher proportion of referrals made in non IPOS areas.
El-Abiary et al.	2021	UK (Scotland)	2010-March 2019	Quantitative retrospective analysis of optometrists and referrals	To identify the distribution of IP optometrists across Scotland and assess the impact of IP on referral rates into HES.	All ocular conditions	Independent prescribing training and qualification	278/1189 (23.4%) community optometrists in Scotland hold IP qualification. In 2019, there was no association between the quantity of IP optometrists and the referral rate to HES (Pearson correlation coefficient $r = +0.53$, $p = 0.052$).

Sii et al.	2019	UK(Scotland)	October–November 2014 (group 1) September–October 2016 (group 2)	Retrospective analysis of 312 (group 1) and 325 (group 2) patients from two areas seen in the HES.	To assess the impact of Scottish Intercollegiate Guidelines Network (SIGN) 144 on quality of referrals from community optometrist	Glaucoma	SIGN 144 Guidelines	**First visit discharge:** Patients referred post-SIGN were less likely to be discharged on their first visit (p=0.004). The overall FVDR declined from 29.2% to 19.4% following the introduction of SIGN guidelines. FVDR pre-SIGN were mainly referrals for high IOP (40%), abnormal optic disc (25%) and abnormal visual field (24%). Post-SIGN guideline implementation, first visit discharges were mainly referrals for abnormal optic disc (31%), abnormal visual field (21%) or both (19%). **Compliance with guidelines:** 86% of referrals post-SIGN implementation were found to be compliant under one or more categories for referral. There was an increase from 36.5% to 53.9% in referrals with repeated IOP readings. There was an increase from 58.8% to 79.6% in IOP using contact tonometry. Visual field assessment repeating increased from 31.7% to 42.8%. Cup: disc ratio measurement increased from 58.8% to 83.6%, and attachment of disc images increased from 7.7% to 36.8%
El-Assal et al.	2015	UK	June 2000–May 2006 (Group A) January 2007–December 2012 (Group B)	Quantitative retrospective audit of new HES glaucoma patient records. Group A (n=835) and Group B (n=737)	To evaluate accuracy and outcome of community optometry referrals after implementation of the new 2006 GOS contract, the 2008 Eyecare Integration Programme pilot and the 2009 NICE guidelines.	Glaucoma	New GOS contract (2006), the Eyecare Integration Programme pilot (2008) and the NICE guidelines (2009)	Waiting times reduced from 12.3(Group A) to 9.4 weeks (Group B). Significantly more patients kept first appointment (p = 0.0002) in group B. At the first hospital appointment 633 eyes (37.6 %) were found to be normal in group A compared to 380 eyes (24.1 %) in group B. There were significantly fewer normal patients (p < 0,0001), more glaucoma suspects (p < 0.0001), more open angle glaucoma patients (p = 0.0006) and fewer other conditions (p = 0.0024) in group B, compared to group A.
Needle et al.	2008	UK	July-August 2006 (6 weeks)	Online survey from 1269 optometrists (including multiple choice and free-text responses)	To investigate optometrists' clinical practice and to elicit their views on the independent prescribing role	All ocular conditions	Independent prescribing training and qualification	Most optometrists felt that, with training, they should be able to prescribe classes of ophthalmic drug (range 58–84%) except for corticosteroids (44.1%). 8% of respondents were currently training for an extended prescribing role. Hospital optometrists expressed the most interest in extended prescribing and were more likely to be either in training (17%) or actively considering training (38%) for supplementary prescribing (p< 0.001 and p= 0.004,

								respectively). The 29% of respondents who were actively considering training were likely to be more recently qualified ($p< 0.001$) 9% said that they had no intention of undergoing further training for prescribing. The most significant barriers to undertaking the training were remuneration (70%), fear of litigation (58%) and the lack of time (64%) or cost of training (61%). Respondents expressed annoyance at the length of placements (% not given).
Dahlmann-Noor et al.	2007	UK	3-month period in 2003 and 7-week period in 2006	Quantitative prospective analysis of 159 referrals and quantitative retrospective analysis of 185 case notes.	To evaluate the quality of the West Suffolk Direct Referral Scheme	All ocular conditions	Six-monthly training sessions and regular feedback via letter about consultation outcomes	99% referrals were appropriate. Diagnostic competence was 87% and improved with tighter communication between HES and optometrists. Agreement remained unchanged for urgency (75%) and decreased for choice of subspecialty clinic from 88% to 74% (due to a larger number of cases being channelled into direct referral clinics for ease of access, despite optometrist's requests for subspecialty appointments)
Patel et al.	2006	UK	June 2002-May 2003	Quantitative retrospective analysis of 376 referrals	To determine if the effect of training intervention on the accuracy of glaucoma referrals and to see if increased numbers of glaucoma cases detected was achieved.	Glaucoma	Training in optic disc assessment and referral criteria every 4 months	58% (376/238) increase in the number of referrals. Positive outcome in 171/376 of referrals (PPV =0.45 (95% CI 0.41–0.51)). From the intervention group 93/183 resulted in a positive referral (PPV = 0.51 (95% CI 0.44–0.58)) From the control group 35/86 were positive referrals (PPV = 0.41 (95% CI 0.31–0.51)). From the non-randomised group 22/59 resulted in positive referral (PPV 0.37 (95% CI 0.26–0.50)).
Theodossiades et al.	2004	UK	June 2000-January 2001	Randomised control trial. 119 referrals control arm and 210 intervention arms. Mixed methods	To test an intervention aimed at improving optometrist case-finding	Glaucoma	Training in optic disc assessment and referral criteria	**Outcomes:** 102/210 of all referrals from the intervention group resulted in a positive outcome (PPV 0.49). 55/119 of all assessed referrals from the control group resulted in a positive outcome (PPV 0.46). **Interviews:** All 13 optometrists reported adopting a more comprehensive analysis of the optic discs since the training. The majority of the 13 reported that they were happy with the content of the training.

Supplementary Table 1: Summary of studies focusing on training and/or guidelines.

Author(s)	Year	Location	Study Period	Scheme	Study Design	Aim	Results
Wang et al.	2021	Australia	July 2016 and June 2019	Non-urgent ocular pathology	Retrospective analysis of 755 patients seen in the CFEH	To evaluate the CFEH integrated eye-care model in the identification of chronic eye diseases within the community.	**Diagnosis**: Approximately half of eye condition-specific appointments at CFEH were glaucoma-related (48.8%) with the majority of remaining appointments consisting of retinal assessments. 77.4% of assessments resulted in the diagnosis of an eye condition or identification of patients at a moderate or high risk of developing eye conditions. 2.6% of patients referred had no evidence of ocular pathology. 15.5% of patients were found to have incidental or concomitant pathology with almost half of this cohort requiring same day intervention. **Management**: 200 (26.5%) were discharged, 432 (57.2%) were recommended monitoring at CFEH and 123 (16.3%) were referred onward to ophthalmology. While most referrals were non-urgent (68.7%), 8.0% required same day referral and 19.6% had a recommended referral time frame within 4 weeks. Most patients requiring onward referral to ophthalmology had their clinical findings confirmed by an ophthalmologist (93.5%) while 1.1% of patients were discharged.
Kanabar et al.	2021	UK	Primary care: 1st June-31st July 2020 Secondary care: 17th June-11th August 2020	Urgent cases	Quantitative retrospective and prospective analysis of referrals.	To evaluate the COVID-19 urgent eye care service (CUES) for primary and secondary care activity.	91.1-91.7% were initially deemed eligible for a telemedicine appointment. 53.3-55.6% were given face-to-face appointments following a telemedicine appointment. 13.0-14.3% of cases were eventually provisionally referred to secondary care HES. Of the 101 provisional referrals to MREH from CUES received, 69 (68.3%) were accepted Of the 61 accepted referrals graded by the hospital clinicians, 39 (63.9%) were categorised as either being in ‘agreement’ or ‘partial agreement’. Of the 32 rejected referrals, 25 (78.1%) were rejected due to the condition not being deemed an emergency 420 telephone calls were recorded and signposted to either CUES, the MREH EED, or local hospitals/optometrist practices. In 56.0% (235 phone calls) the patient was advised to attend MREH EED and in 32.4% (136 phone calls) the patient was advised to see a CUES optometrist in the community.

Huang et al.	2020	Australia	March 2015-June 2018	Glaucoma	Quantitative retrospective, analysis of 252 glaucoma referrals	To examine the impact of referral source (community optometrists vs RR) on patient glaucoma management	A significantly higher proportion of patients were confirmed with a glaucoma diagnosis following referral refinement (43.8%) compared to community referrals (27.0 %, p = 0.008) PPV for referral refinement was 51% (90/178) and 34% (25/74) for community referrals. False positive referral rates were 4% for referral refinement (8/178) and 26% (19/74) for community referrals. Patients having undergone referral refinement were more likely to result in treatment initiation compared to those referred directly from a community optometrist (p = 0.016)
Phu et al.	2020	Australia	Pre-suite August 2017-February 2018 Post-suite/angle suite March 2018-August 2018	Glaucoma (Angle suite)	Quantitative retrospective analysis of patients seen pre (n=383) and post (n=425) introduction of a referral pathway for anterior chamber angle assessment (Angle Suite). Patients seen via the angle suite were also analysis (n=77).	To evaluate a newly developed referral and collaborative care pathway specifically for patients with angle closure spectrum disease	**Waiting times:** Angle Suite patients had a significantly shorter time to appointment compared to both Pre Suite and Post Suite groups (p< 0.0001). Post Suites had a shorter time to appointment to Pre Suites (p = 0.0002). The Post Suite cohort had an approximately one-third reduction in angle closure diagnosis compared to the Pre Suite cohort (6.6% vs 4.0%, p = 0.1189) 13.6% of patients had a stage of angle closure disease that required prompt intervention in the Pre Suite and 9.3% in the Angle Suite groups. No patient in the Post Suite group required urgent referral. The true negative rate (open angles mentioned in the letter and open angles found) was 100% (28/28) for the Pre Suite and 92.9% (52/56) for the Post Suite plus Angle Suite. The true positive rate (narrow angles mentioned in the letter and angle closure glaucoma spectrum disease found) was 73.1% (19/26) for the Pre Suite and 70.1% for the Post Suite plus Angle Suite (54/77). The proportion of cases diagnosed with angle closure spectrum disease in the Pre and Post period where the angle was not described in the referral letter were 37.5% (9/24) and 75.0% (12/16), respectively.

Ford et l.	2019	Australia	Standard pathway: October 2014-April 2017 C-EYE-C pathway January 2017–October 2017	Glaucoma	Retrospective clinical and financial audit o 182 standard pathway referrals and 321 C-EYE-C referrals	To determine whether C-EYE-C improves access to care and better utilises resources, compared to hospital-based care.	**Waiting times:** The C-EYE-C model demonstrated a significantly shorter median wait-time from referral to first appointment of 89 days compared to 386 days for standard care (p < 0.001.) **Outcomes:** The total proportions of patients diagnosed as a glaucoma suspect, with definitive glaucoma, or glaucoma with additional ocular pathology was 76% for the standard pathway and 90.9% for the C-EYE-C. Over half of the patients in both standard pathway and C-EYE-C (57.6% Vs 56.5%) required routine follow-up (>3 months) **Appointments avoided:** There were 148 hospital outpatient appointments avoided by patients that attended the C-EYE-C clinic for the first encounter. Assuming that the outpatient clinic has 14 glaucoma appointments available each week for new patients, then 10.6 weeks of appointments were saved by assessing patients off-site at C-EYE-C. **Diagnostic agreement**: Absolute agreement between C-EYE-C and virtual ophthalmologist was 68% and a 95% weighted agreement (k = 0.69). For patient management decisions the absolute agreement was 79%, with a weighted agreement of 95% (k = 0.66). For cases where the optometrist's recommendation was changed, 7.6% required more urgent care, and 13% less. Numbers of patients discharged did not change.
Gunn et al.	2019	UK	October 2014-August 2016	Glaucoma	Prospective, quantitative analysis of 1404 patients evaluated in GERS	This evaluates the clinical effectiveness of the Manchester Glaucoma Enhanced Referral Scheme (GERS).	**False positives:** The FP rate (patients discharged at first visit) was 15.5% (44/283) 54.1% (153/283(were monitored in the HES without treatment, 27.6% (78/283) were monitored with treatment, 3.2% (9/283) required further investigation. **False negatives:** 89.3% (117/131) seen by the GERS and not referred were confirmed as not requiring hospital follow-up.10.7% (14/131) required follow-up, including 5 (3.8%) offered treatment. Only one patient (0.8%) in this sample met the GERS referral criteria and was not referred (true FN)
Konstantakopoulou et al.	2018	UK	September 2013-August 2014	MECS	Quantitative prospective analysis of 2123 patients	To monitor the activity and evaluate the clinical safety of a MECS	75.1% (1595/2123) of MECS patients remained within community optometric practice; 64.0% (n=1359) were diagnosed with pathology and managed in the community. 11.1% (236/2123) were found to have no pathology and discharged. 5.7% (122/2123) were referred to their GP and 18.9% (400/2123) were referred to the HES. 49.1% were routine, 22.6% urgent and 28.3% emergency For a sample MECS assessments reviewed by the research team, 5.5%

					evaluated in the MECS		(12/220) were rated as inappropriate. 3(1.36%) patients rated as inappropriate management could have come to harm by the optometrists' management 89.2% were judged to have been appropriately referred and 78.2% were referred with appropriate urgency.
Ly et al.	2017	Australia	1st July 2013-30th June 2016	Pigmented lesions	Quantitative retrospective review of 182 patients referred to an intermediate-tier clinic (CFEH).	To describe the referral patterns of pigmented lesions to an optometry led intermediate-tier collaborative clinic.	**Diagnosis**: Choroidal naevus was the suspected diagnosis in 58% (105/182) and CFEH diagnosis in 59% (107/182). The number of cases without a specific diagnosis was reduced by approximately two-thirds (29% to 10%) after assessment at the CFEH. **Management:** The CFEH report most frequently recommended recall for CFEH review (53%, 96/182), followed by discharge (35%, 64/182), or referral to an ophthalmologist (12%, 22/182).
Ly et al.	2016	Australia	1st July 2013-30th June 2014	non-urgent macular disease	Quantitative retrospective review of 291 patients referred to an intermediate-tier clinic.	To appraise the optometric referral patterns of patients with suspected macular disease to an intermediate-tier optometric imaging clinic	**Diagnosis:** The most common diagnoses suspected by primary care optometrists was non-neovascular AMD (75, 26%), CSCR (22, 8%) and ERM (8, 6%). 3 cases were referred to confirm that the macula was normal. AMD was the most common diagnosis (93, 32%) after assessment at CFEH, followed by other (54, 19%), ERM (22, 8%), normal aging changes (21, 7%), no apparent defect (NAD; 22, 8%) and CSCR (13, 4%). The number of cases without a diagnosis was halved (reduced from 47% to 23%). Cases with NAD rose from 1% to 8%. 121/291 (42%) referrals stipulated a suspected diagnosis that was confirmed after evaluation at CFEH **Management:** 244/291 (84%) patients were recommended ongoing optometric care: with the referring optometrist (57/291, 20%) or through recall to CFEH (187/291, 64%). Referral to an ophthalmologist was recommended in 47/291 (16%).
Konstantakopoulou et al.	2016	UK	September 2013-August 2014	MECS	Retrospective, quantitative analysis of 2123 MECS appointments. Qualitative	To evaluate the clinical effectiveness, impact on hospital attendances and patient satisfaction with MECS	**Outcomes:** 64.1% were managed by optometrists and 11.2% were discharged with no ocular pathology. 18.9% of patients were referred to the HES, of which 49.1% were referred routinely, 22.6% urgently and 28.3% emergency. Based on a consensus panel assessment 95% (208/220) of a sample were appropriately managed. **Management agreement:** 89.2% were judged as referred appropriately and

					analysis of patient satisfaction questionnaires.		78.2% were referred with appropriate urgency. For inappropriate referrals, in over 90% these were referred with greater urgency than required. First attendances to the HES referred by GPs dropped by 26.8% and follow-up appointments fell by 12.9% in the areas operating the MECS scheme compared to the comparison area.
McAlinden et al.	2016	UK	February 2012	WEHE and PEARS	Quantitative prospective analysis of 2302 patients seen in the WEHE or PEARS scheme.	To assess the demographics of patients accessing WEHE/PEARS, referral patterns and clinical management.	**Outcomes:**27.8% (640/2302) required no further action and were discharged. 43.3% (997/2302) required monitoring by their optometrist or ophthalmic medical practitioner, 15.9% (367/2302) required referral to the HES, 7.3% (168/2302) required referral to the GP. The GP was informed in 53.2% (1223/2302)
El-Assal et al.	2015	UK	June 2000–May 2006 (Group A) January 2007–December 2012 (Group B)	New GOS contract (2006), the Eyecare Integration Programme pilot (2008) and the NICE guidelines (2009)	Quantitative retrospective audit of new HES glaucoma patient records. Group A (n=835) and Group B (n=737)	To evaluate accuracy and outcome of community optometry referrals after implementation of the new 2006 GOS contract, the 2008 Eyecare Integration Programme pilot and the 2009 NICE guidelines.	Waiting times reduced from 12.3(Group A) to 9.4 weeks (Group B). Significantly more patients kept first appointment ($p = 0.0002$) in group B. At the first hospital appointment 633 eyes (37.6 %) were found to be normal in group A compared to 380 eyes (24.1 %) in group B. There were significantly fewer normal patients ($p < 0,0001$), more glaucoma suspects ($p < 0.0001$), more open angle glaucoma patients ($p = 0.0006$) and fewer other conditions ($p = 0.0024$) in group B, compared to group A.
Roberts et al.	2015	UK	February 2005-February 2009	Glaucoma	Quantitative retrospective analysis of 1639 patients seen in the refinement scheme.	To report on results of a glaucoma shared-care scheme based in Peterborough, UK.	**Waiting times**: The median waiting time between referral and SOG assessment was 0 days and the median time between SOG assessment and ophthalmologist evaluation was 12 days, **Diagnosis:** 18.3% of patients were diagnosed with glaucoma, and in 5.8% no pathology was found. Most patients (65.4%) were diagnosed as glaucoma suspects, had OHT or risk factors for glaucoma. A minority were found to be at risk of angle closure or had other pathology (5.6 and 1.5%, respectively).

							Diagnostic agreement: Level 2 SOGs had 64.6% agreement with a consultant, 23.2% non-significant disagreement, 5.6% disagreement. Level 1 SOGs had 47.5% agreement, 28.4% non-significant disagreement, 15.3% disagreement. **Outcome**: Level 2 SOGs had a 69.5% agreement, falling to 49.1% in the Level 1 SOGs. Non-significant disagreement was 18.7 and 21.0% and disagreement was 10.4% and 28.6% in for Level 2 and Level 1 SOGs respectively. **Sensitivity/specificity**: Level 2 SOG's had a sensitivity of 61.0% and a specificity of 75.2%. The sensitivity and specificity of Level 1 SOGs was 53.8% and 64.8%.
Keenan et al.	2015	UK	1st April 2010- 31st March 2013	Glaucoma	Retrospective, quantitative analysis of 1733 patients seen as part of the refinement scheme.	To describe outcome data from the Cambridge community Optometry Glaucoma Scheme (COGS)	Following assessment, 46.6% (n= 807) patients were discharged by an OSI. **Management agreement:** Consultant ophthalmologist agreement with OSI management decisions was 91.5%. Following virtual review of patient data, a further 5.7% (n= 99) patients were discharged. Virtual review resulted in 3.6% of all patients (n= 62) who had been discharged following community OSI assessment being recalled to the HES. Following further assessment in consultant-led clinic, 11 of the recalled patients were discharged at first visit. Of the 111 OSI referrals for an occludable anterior chamber angle, the consultant ophthalmologist found 43 (38.7%) patients to have narrow angles on gonioscopy.
Ratnarajan et al.	2015	UK	__	Glaucoma	Retrospective quantitative assessment 120 seen in a glaucoma referral refinement scheme.	To establish the safety of the CHANGES glaucoma referral refinement scheme (GRRS).	46/120 (38%) of patients seen in the glaucoma refinement scheme were discharged and 34/46 (74%) of the agreed to attend a HES review by the glaucoma consultant. **Management agreement:** The glaucoma consultant found all 34 patients to have GAT IOP measurement below the JCG threshold for discharge. 5/34 (15%) were found by the consultant to have a suspicious optic nerve following slit lamp biomicroscopy, were classified as 'glaucoma suspect' and offered a follow-up appointment. This translates to a 'missed glaucoma rate' of 0% and a false negative rate of 15% for the OSI. This rate is not for the CHANGES scheme as a hospital optometrist virtually reviews the digital images of all optic discs of patients discharged.

jan et al.	2013	UK	March-April 2011	Glaucoma	Retrospective, quantitative, multisite analysis of 271 patients (from Huntingdon, Manchester, Gloucestershire and Nottingham).	To compare glaucoma referral refinement schemes (GRRS) in the UK during a time period of considerable change in national policy and guidance.	For OSIs, first visit discharge rate (FVDR) 17.2% For non-OSIs FVDR was 43.9% The largest source of first-visit discharges for both non-OSIs and OSIs was for IOP-only related referrals (83.5% and 55% respectively)"
Ratnarajan et al.	2013	UK	August 2006-June 2011	Glaucoma (referral refinement with shared care)	Quantitative retrospective audit of 912 glaucoma referrals	To assess the impact of referral refinement criteria on the number of patients referred to, and first-visit discharges from, the HES	**Raised IOP:** 429 referrals from community optometrists were due to raised IOP (22–28 mmHg), of which 34% were discharged by the OSI. 38 referrals were for IOP asymmetry >5 mmHg of which 45% were discharged by the OSI. **Abnormal optic disc**: 207 referrals from community optometrists were for an abnormal optic disc alone, of which 37.7% were discharged by the OSI. **Abnormal VF**: 84 referrals from community optometrists were for an abnormal VF alone, of which 51% were discharged by the OSI. **JCG guidance:** 51/70 (73%) patients who were aged between 65–80 and 6/10 (60%) who were aged over 80 and had been referred by OSIs on the basis of raised IOP only would have satisfied the JCG criteria for non-referral.
Parkins and Edgar	2011	UK	April 2007-April 2008	Glaucoma	Quantitative retrospective analysis of glaucoma referrals seen via one of referral schemes (209 from repeat measures and 218 for referral refinement).	To compare the clinical and financial effectiveness of two optometric-led enhanced glaucoma referral schemes	**Repeat Measures:** 50 (24%) patients were referred on to the HES. In 57 (44.5%) of the 128 cases where raised IOP by NCT was found repeated measurement by Goldmann/Perkins applanation tonometry resulted in lower readings of 21 mmHg or less, or less than a 5-mmHg difference between the two eyes. **Referral Refinement**: After reviewing initial referrals, 111 patients (51%) were referred direct to the HES and 107 to the refinement scheme. The scheme referred 12/107 (11%) patients for investigation for suspect glaucoma. They discharged 76 patients (71%) and booked 15 for further refinement. Ten of these patients were subsequently discharged.

Devarajan et al.	2011	UK	4-year period	Glaucoma	Retrospective analysis of 100 patients referred to the HES via, and 100 patients discharged from a refinement scheme.	To describe a community glaucoma refinement scheme.	**Outcomes:** 83% of all referrals from the refinement scheme were either diagnosed immediately with glaucoma or retained in the clinic for follow-up investigation. Of the 14 'normals', only 5 were immediately discharged, Visual-field abnormalities were diagnosed in 51% on referral, compared to 43% in the HES. **False negative rate**: All patients in the sample of discharged patients (n=100) were found to have followed the agreed protocols. Of the 98 virtually reviewed discharged patients, consultant ophthalmologists were in agreement with the referring optometrist 50% of the time, suggested overestimation of CDR for 35% of images, and underestimation for 15% (of which 2 showed changes that merited recall to the HES for investigation, but neither were started on treatment. This translates as a false-negative rate of 3-10%.
Syam et al.	2010	UK	February 2005-March 2007	Glaucoma	Retrospective, quantitative analysis of 1184 glaucoma referrals and 72 patient satisfaction surveys.	To assess the role of specialist optometrists working in the community shared care for glaucoma patients.	**Waiting time**: Average waiting time from referral to SOG assessment was 36 days and between SOG assessment to HES evaluation was 15 days. **Diagnostic agreement**: A significant disagreement between the appraisal and findings of the SOGs was observed in optic nerve morphology (11%), visual field (7%), diagnosis (12%), treatment (10%), and follow-up (17%) 68% of patients were followed up in the community. 32% of patients were referred to the HES.
Bourne et al.	2010	UK	25th August 2006 -31st December 2007	Glaucoma	Quantitative prospective assessment of 121 referrals triaged into and seen by a referral refinement scheme	To describe the design, activity, and quality of the referral refinement phase of a novel glaucoma shared-care scheme	The OSI discharged 35% 40/121 of patients seen. **Management agreement**: A consultant agreed (virtually) with the decision to discharge in 28/40 (70%). Compared to a consultant, OSI sensitivity for suspicious optic discs was 78%, specificity 61% and NPV 79%. OSI sensitivity for an IOP of >21 mmHg was 74%, specificity 85, and NPV 90%. OSI sensitivity for an occludable anterior chamber angle (Van Herick Vs gonioscopy) was 69%, specificity 88%, and NPV 94%. **Longitudinal:** When separating into two 8-month period to test for change over time, significantly fewer false positives were made by the OSI in the more recent 8-month period for IOP measurements only (p= 0.015).

Ang et al.	2009	UK	Pre-GOS June-November 2005 Post-GOS June-November 2006	Glaucoma	Retrospective quantitative study of 183 referrals made during the first 6-month period and 120 referrals made during the second 6-month period.	To assess the quality of referrals from community optometrists in the Scotland to the HES before and after the implementation of the new General Ophthalmic Services (GOS) contract	**Patient outcomes:** The number of true-positive referrals after the new GOS contract 38/120 (31.7%) compared to before it was introduced 33/183 (18.3%) (p=0.006). The proportion of patients discharged at the first visit was less post-GOS introduction 20/120(16.7%) compared to before it was introduced 79/183(43.2%) (p=0.004). **Quality of referrals:** post-GOS introduction, there was an improvement in the number of referrals with applanation IOPs (p=0.000), dilated fundal examination (p=0.000), and repeat VFs (p=0.004). Referrals with optic disc assessment and documentation of family history of glaucoma were lower (p= 0.017 and 0.050, respectively). Less than half (41.7%) fulfilled the new GOS (Scotland) contract requirements. The most common examination missing in the referral was applanation tonometry
Sheen et al.	2009	UK	April-December 2006	PEARS and WEHE	Quantitative prospective analysis of 6432 patients and telephone interviews with a subset of 289 patients.	To derive an evidence, base for the efficacy of two optometric primary eye care services in Wales (PEARS and WEHE)	**Overall:** 66% (4243/6432) were managed in optometric practice without referral. 18% (1171/6432) were referred to the HES; and 16% (1018/6432) were referred to the GP, either for co-management (415; 41%) or for systemic investigation (603; 59%). **Patients referred to HES**: 75% were deemed to have been appropriately managed by the optometrist and 72% (284/392) correctly diagnosed. 73% (286/392) attended for at least two follow-up HES visits. Of the remaining 106, 85 (22%) were discharged at the first visit without treatment.
Henson et al.	2003	UK	_	Glaucoma	A quantitative retrospective analysis of 194 patients who had passed through the refinement scheme.	To describe a glaucoma referral refinement scheme and report the first year's results and its financial costs to the NHS.	**Outcomes:** 58% (112/194) of patients seen within the scheme were referred to the HES.

Supplementary Table 2: Summary of studies focusing on the clinical impact of enhanced referral refinement schemes.

Author(s)	Year	Location	Study Period	Scheme	Study Design	Aim	Results
Wang et al.	2021	Australia	July 2016 and June 2019	Non-Urgent ocular pathology	Quantitative retrospective analysis of 755 patients seen in the CFEH	To evaluate the CFEH integrated eye-care model in the identification of chronic eye diseases within the community.	**Cost:** The average cost per patient assessment was 245 AUD. With an average rebate of 50.26 AUD from Medicare, the net cost of an eye disease assessment at CFEH is 195.50 AUD. There is no apparent cost reduction compared to the public hospital system.
Forbes et al.	2019	UK	April 2013-November 2016	Glaucoma	Cost analysis of 2405 patient appointments	To examine the cost consequences of the Manchester Glaucoma Enhanced Referral Scheme (GERS) by considering the total costs of the scheme	Assuming 2.3 outpatient visits to the HES avoided per person: NHS cost saving of £6635 (approx. £2.76 per patient passing through the scheme). Assuming 1 HES outpatient visit was avoided per person, there was no cost saving and costs £101690 (approx. £42.28 per patient within the scheme) Patients need to have an average of 2.22 visits to the HES prior to discharge to make the GERS scheme cost neutral
Ford et l.	2019	Australia	Standard: October 2014-April 2017 C-EYE-C January 2017–October 2017	Glaucoma	Retrospective clinical and financial audit of 182 standard pathway referrals and 321 C-EYE-C referrals	To determine whether C-EYE-C improves access to care and better utilises resources.	**Cost Analysis:** The average cost per patient encounter was $171.00 for the hospital model, and $133.16 for C-EYE-C
Mason et al.	2017	UK	2nd September 2013-30th August 2014	MECS	Retrospective audit, with cost analysis of MECS scheme compared to a control area. Difference-in-difference comparison.	To examine how the introduction of MECS affected the numbers of patients treated by the HES and the cost consequences	**Intervention area 1**: Total costs for HES and ITS activity were 2.5% higher in 2013–2014 (post-intervention) compared with 2011–2012(pre-intervention). **Intervention area 2**: Total costs for HES and ITS activity were 13.8% lower in 2013–2014 (post-intervention) compared with 2011–2012(pre-intervention) **Control area**: Total costs for HES and ITS activity were 3.1% higher in 2013–2014 (post-intervention) compared with 2011–2012(pre-intervention)
Ratnarajan et al.	2013	UK	August 2006-June 2011	Glaucoma	Retrospective audit of 912 glaucoma referrals	To assess the impact of referral refinement criteria on the number of patients referred to, and first-visit discharges from, the HES	**Cost analysis:** The number of patients attending the HES was reduced by 15% in 2010. The cost saving of the CHANGES scheme was £16 258, which represents a 13% reduction compared to if all patients were seen directly by the HES.

Devarajan et al.	2011	UK	4-year period	Glaucoma	Quantitative retrospective analysis of 100 referred to the HES via, and 100 discharged from a refinement scheme.	To describe a community glaucoma refinement scheme.	**Cost Analysis:** The scheme resulted in a 53% reduction in the total number of referrals to HES with a cost saving of £117 per patient.
Parkins and Edgar	2011	UK	April 2007-April 2008	Glaucoma	Quantitative retrospective analysis of all glaucoma referrals seen via one of two referral schemes (209 from repeat measures and 218 for referral refinement).	To compare the clinical and financial effectiveness of two optometric-led enhanced glaucoma referral schemes	**Repeat Measures:** The cost saving for the scheme was calculated as £17067 (62%) for the 209 patients, compared to if they were seen at the HES on first visit. **Referral Refinement**: The cost saving for the scheme was calculated as £1022 (3.5%) for the 218 patients, compared to if they were seen at the HES on first visit.
Sheen et al.	2009	UK	April-December 2006	PEARS and WEHE	Prospective, quantitative analysis of 6432 patients and telephone interviews with a subset of 289 patients.	To derive an evidence, base for the efficacy of two novel optometric primary eye care services in Wales	**Cost**: The net cost of the 6423 examinations over the 8- month period was approximately £77 000, or a cost of approximately £12 per PEARS or WEHE consultation. A cost model based upon a 50% referral to the HES with the remainder consulting the GP on two further occasions yields a cost of approximately £15 per PEARS or WEHE consultation
Henson et al.	2003	UK	_	Glaucoma	A retrospective analysis of 194 patients who had passed through the refinement scheme.	To describe a glaucoma referral refinement scheme and report the first years' results and its financial costs.	The cost saving works out to be approximately £17 per patient passing through the scheme. This is assuming that the training programme will have to be repeated every 3 years and that the scheme will continue to see 23 patients/month and 42% of these will not be referred to the HES.

Supplementary Table 3: Summary of studies focusing on the cost-effectiveness of enhanced referral refinement schemes.

Author(s)	Year	Location	Study Period	Scheme	Study Design	Aim	Results
Barrett and Loughman	2018	Ireland	_	Glaucoma and MECS	Qualitative study using an anonymous survey from 199 optometrists.	To explore optometrists' attitudes towards an enhanced scope of clinical practice	**Optometrists:** 4/199 participants (2.1%) indicated 'no interest in changing the scope of the traditional eye examination', the remainder indicated varied levels of interest in expanding their scope of practice. 68% of respondents indicated an interest in shared care for diabetic retinopathy. 67% were interested in providing pre/post-operative cataract services. 61% were willing to become involved in shared care schemes for AMD. 47% indicated interest in expanding their role in paediatric services.
Baker et al.	2016	UK	During 2014-2015	Glaucoma	Qualitative study of 189 patients, 25 community optometrists, 4 glaucoma specialist hospital optometrists, 5 ophthalmologists, 6 GPs and 4 commissioners using surveys, interviews and focus groups.	To explore views of all stakeholders regarding the operation of community-based enhanced ophthalmic services	**Patients**: 99% (GRRS) and 100% (MECS) of patients were satisfied with the examination. 99% of MECS patients would recommend the service. 95% of participants in both schemes had confidence and trust in their optometrist **Optometrists** were enthusiastic about GRRS, feeling fortunate to practise in a 'pro-optometry' area. No major negatives were reported, although both schemes were limited to patient's resident within certain areas, and some inappropriate GP referrals occurred (MECS). Communication with hospitals was praised in GRRS but was variable, depending on hospital for MECS. Training for both schemes was valuable and appropriate but should be ongoing. **GPs**: were very supportive, reporting the scheme would reduce secondary care referral numbers, although some MECS patients were referred back to GPs for medication. **Ophthalmologists** expressed positive views and acknowledged that new care pathways would reduce unnecessary referrals and shorten patient waiting times. **Commissioners** felt both schemes met or exceeded expectations in terms of quality of care and allowing patients to be seen quicker and more efficiently.
Konstantakopoulou et al.	2016	UK	September 2013-August 2014	MECS	Retrospective, quantitative analysis of 2123 MECS appointments. Qualitative analysis of patient questionnaires.	To evaluate the clinical effectiveness, impact on hospital attendances and patient satisfaction with MECS	All patients (100%) (109/109) who completed the survey were satisfied with their visit to the optometrist and 99% would recommend the scheme to a friend;95% of the patients reported confidence and trust in their MECS optometrist and 90% were satisfied with the location they attended.
Konstantakopoulou et al.	2014	UK	_	Glaucoma and MECS	Qualitative study of 43 optometrists, 6 ophthalmologists and 25 GPs using free-text questionnaires and telephone interviews.	To explore the views of optometrists, GPs and ophthalmologists regarding community-based enhanced optometric services	**Optometrists**: Most common reason for participating in extended role programmes was for career development. Another reason for participation was the perceived benefit for patients and the wider NHS through improving pathways and enhancing glaucoma detection. 40% reported that participation was a means of receiving remuneration for services. Approximately 85% identified that training had a beneficial effect on their practice. Optometrists felt that MECS would improve communication with secondary eye care services. Non-participating optometrists believed that participating in the scheme would have required their practice to adapt significantly. **Ophthalmologists:** Ophthalmologists participated for reasons that were more patient centred: reduction of unnecessary referrals, relieving patient anxiety, improving patient care and reductions in patient waiting times

							GPs: Almost all GPs thought MECS would improve care and 'journey' for patients, as well as reduce waiting times. GPs believed that the scheme offers patients more choice and provides a cost effective and accessible service.
Syam et al.	2010	UK	February 2005-March 2007	Glaucoma	Retrospective, quantitative analysis of 1184 glaucoma referrals and 72 patient satisfaction surveys.	To assess the role of specialist optometrists working in the community shared care for glaucoma patients.	**Patients**: 96% (69/72) of returned questionnaires indicated satisfaction with the scheme 9 patients expressed some confusion about the details of their follow-up appointment.
Sheen et al.	2009	UK	April-December 2006	PEARS and WEHE	Prospective analysis of 6432 patients. Interviews with a subset of 289 patients.	To derive evidence for the efficacy of two optometric care services in Wales (PEARS and WEHE)	**Patients:** Of the 289 interviewees, 94.8%) were ''very satisfied'' and 15 (5.2%) ''fairly satisfied'' with the optometric service. 87.4% travelled less than 5 miles to an optometrist.

Supplementary Table 4: Summary of studies focusing on the acceptability of enhanced referral refinement schemes.

Author(s)	Year	Location	Study Period	Study Design	Aim	Results
Bowes et al	2018	UK	April-December 2015	Prospective, quantitative study of 712 direct referrals for cataract surgery	To report on defined key performance indicators (KPIs) of a cataract shared care scheme.	**Listing rates**: 591/712 patients (83%) were listed for cataract surgery at first visit. Of 449 GP routine clinical pathway referrals 282 patients (63%) were listed at first consultation. **Outcomes:** Of the 569 patients who had surgery(n=569), 402(71%) were discharged back to the community, 116 (20%) were followed up in a doctor-led clinic and 51 (9%) were followed up in a hospital optometrist led clinic.
Park et al.	2009	UK	March-May 2006	A quantitative retrospective analysis of patients referred for cataract surgery (62 via optometric pathway and 62 via GP pathway)	To compare the quality of referrals and listing rates of direct optometric referrals vs traditional GP referrals for cataract surgery.	**Referral content**: Direct referrals were more likely to include information relating to objective visual loss (100 vs 87%, p= 0.0061) and to counsel the patient (97 vs 18%, p=0.0001). GP referrals were more likely to comment on personal circumstances (32 vs 3%, p=0.0001), past medical history (95 vs 68%, p=0.0001), and drug history (94 vs 69%, p= 0.0009). **Operative rates:** Direct referrals had higher operative rates (87 vs 69%, p=0.0284). More patients from the traditional GP pathway were not listed, because the cataract was found to have no effect on their lifestyle (12 GP pathway, 4 direct pathway), or because the patient declined surgery (4 GP pathway, 2 direct pathway), or for other reasons (3 GP pathway, 2 direct pathway).
Lash et al.	2006	UK	4th October- 6th December 2004 (2 months)	Quantitative prospective audit 351 optometrist referrals for cataract (162 GOS18 143 direct, 61 letters)	To review three types of optometrist referral (direct, GOS 18 and by letter) for information included and listing rates for surgery.	**Information included:** Full information was included in all direct referrals,10% (n=16) of GOS 18 referrals and 17% (n=8) of letter referrals. **Listing rates:** The listing rates were 83%(n=119) for direct referrals, 78% (n=36) for letter referrals and 73% (n=117) for GOS18 referral p (chi-squared test P=0.087)

Supplementary Table 5: Summary of studies focusing refinement schemes for cataract referrals

Author(s)	Year	Location	Study Period	Study Design	Aim(s)	Condition(s)	Imaging used	Main Results
Al Harby et al.	2022	UK	June 2016-July 2017	Prospective quantitative study of 400 patients attending naevus clinics.	To present the results of the NAEVUS study on a large prospective cohort to validate a virtual model for managing choroidal naevi referrals in terms of its safety	Naevo-melanocytic lesions	Wide-field colour imaging, auto-fluorescence imaging (AF), optical coherence tomography (OCT) and B-scan ultrasound	Agreement for management decisions between face-to-face and virtual pathways was 83.1% (non-medical) and 82.6% (medical). There were more over-referrals in the virtual pathway (non-medical 24.3%, medical 23.3% of gold standard discharge) and only two under-referrals (10.5% of gold standard referrals), both borderline cases with minimal clinical risk. The agreement for risk factors of growth (orange pigment, subretinal fluid, hyper-AF) ranged between 82.3% and 97.3%
Hind et al.	2022	UK	?	Prospective quantitative study of 97 patients referred for suspect lid-lesions.	To assess the accuracy and feasibility of a pilot service by determining whether photograph-based assessment could be validated against a face-to-face clinic consultation	Eyelid lesions	External eye photographs	There was substantial agreement between diagnosis reached by clinicians reviewing patients F2F (Arm A) and clinicians reviewing photographs taken by a clinical photographer (Arm B (K = 0.72) and also between Arm A and clinicians reviewing photographs taken by a trained optometrist Arm C (K = 0.79) There were 10 lesions identified on F2F clinic review as suspected malignancy. All of these 10 lesions were also identified as suspicious by the clinicians reviewing the images from both Arm B and Arm C. There was substantial agreement in determining malignancy between Arm B and Arm A (K = 0.7) and almost perfect agreement between Arm C and Arm A (K = 1.0) 40% of patients were discharged without surgical intervention from the clinic. In Arm B, discharge was recommended in 51.6%, whereas in Arm C it was recommended in 28.4%. These differences were not statistically significant (Arm B vs A p = 0.145 and Arm C vs A 0.09).
Muttuvelu et al.	2021	Denmark	1st August 2018-31st July 2019	Quantitative retrospective analysis of 9938 referrals made to a web-based referral platform	To evaluate follow-up and referral patterns after implementing a telemedical service for suspected	Posterior segment	Fundus photography	Mean time from routine referral to ophthalmologist review was 29 hours Mean time until optometrists communicated the review results to patients was 55 hours The average non-acute patient journey time was 115 hours,18 minutes 19.5% (n=1938) of the patients were referred onwards to the Danish national eye service. 14.4% (n=1431) of the referrals in did not need any further follow-up.

					posterior segment pathology			66.1% (n=6569) needed follow-up either by the optometrist (46.8% (4651 patients)) or within the TS (19.3% (n=1918))
Kern et al.	2020	UK	April 2018-January 2019	Quantitative retrospective analysis of 103 patients referred using a web-based referral platform	To report the implementation and initial results of a cloud-based referral platform to the HES	Retinal	Fundus photograph and OCT scan	54 (52%) of the patients classified into the referral pathway did not require specialist referral 14 (14%) patients were reviewed as urgent and 35 patients (34%) as routine. For 7 (7%) patients, a diagnosis could not be made on clinical history and OCT scans alone The mean overall time for optometrists was 9.2min per patient The mean review time for referral refinement by an ophthalmologist was 3.0min in total
Kortuem et al.	2018	UK	September 2016-May 2017	Quantitative retrospective analysis of 186 patient referrals	To report on the implementation and integration of virtual medical retina clinics	Retinal	Fundus photographs and OCT scan	The average waiting time for was 45.3 days (SD +/- 27.6 days) 46.8% of patients were reviewed for diabetic eye disease followed by dry AMD (10.2%) 45.5% of patients were discharged at first visit. 37.1% had virtual follow up and 17.4% required a F2F appointment. The most common reason for a referral to a face-to-face clinic was poor image quality.
Kotecha et al.	2017	UK	1st March 2014-31st March 2016	Quantitative retrospective analysis of 1380 patients attending a virtual glaucoma clinic	To describe the outcomes of a technician-delivered glaucoma referral triaging service with virtual review data by a consultant ophthalmologist	Glaucoma	Stereo fundus imaging and anterior angle OCT	The average (SD) journey time in the clinic was 58 (16) min. The average (SD) time from patient attendance to consultant virtual review was 4 (4) days The number of patients discharged following virtual review was 855 (62%) 16 patients (1%) required same-day doctor assessment due to elevated IOP. 91 (6%) patients were booked for a follow-up in the glaucoma monitoring virtual clinic. 418 patients were referred for face-to-face outpatient review. 66/82 patients reviewed to assess false negative rate were discharged following consultation, equating to a false-negative rate of 20%.
Balaskas et al.	2016	UK	October 2014-March 2015	Retrospective quantitative analysis of results from 102 patients attending naevus clinics.	Pilot study to test the safety and validity of a one-stop virtual clinic model relying on allied health professionals	Naevo-melanocytic lesions	Wide-field colour imaging, auto-fluorescence imaging (AF), optical	Agreement for management decisions between gold standard and grader was 96.1% (98/102) Agreement for management between gold standard and ophthalmologist was 100% (102/102) Agreement in the rate of pick of erroneous referrals (i.e. nonchoroidal naevo-melanocytic lesions) between gold standard and masked grader was 98% (100/102)

					assessing naevomelanocytic lesions		coherence tomography (OCT) and B-scan ultrasound	The agreement rate between masked ophthalmologist and masked grader was 94% for the presence of orange pigment detected on photographs, 97% for location of the lesion within one disc diameter of the optic disc, 93% for the presence of increased AF, 95% for increased AF attributable to drusen only or related to lipofuscin/subretinal fluid, 100% for the presence of subretinal fluid on OCT and 98% for the presence of choroidal elevation on OCT.
El-Assal et al.	2015	UK	June 2000–May 2006 (Group A) January 2007–December 2012 (Group B)	Quantitative retrospective audit of new HES glaucoma patient records. Group A (n=835) and Group B (n=737)	To evaluate accuracy and outcome of community optometry referrals after implementation of the new 2006 GOS contract, the 2008 Eyecare Integration Programme pilot and the 2009 NICE guidelines.	Glaucoma	Optic disc photographs and visual field plots.	Waiting times reduced from 12.3(Group A) to 9.4 weeks (Group B). Significantly more patients kept first appointment ($p = 0.0002$) in group B. At the first hospital appointment 633 eyes (37.6 %) were found to be normal in group A compared to 380 eyes (24.1 %) in group B. There were significantly fewer normal patients ($p < 0,0001$), more glaucoma suspects ($p < 0.0001$), more open angle glaucoma patients ($p = 0.0006$) and fewer other conditions ($p = 0.0024$) in group B, compared to group A.
Goudie et al.	2014	UK (Scotland)	September 2010 - January 2011	Quantitative, retrospective analysis of 358 e-referrals with attached digital images.	To quantify the effect of attaching digital images to ophthalmic referrals.	All ocular conditions	Fundus photographs	All 358 images were of a quality that could be used to influence clinical decision making 53 referrals (18%) were deemed 'urgent' and were seen within 24–60 h 122 referrals (34%) did not result in an appointment with the HES, with 95 (25% of total) resulting in an 'e-diagnoses. 2/254 patients (0.8%) who were given an appointment 'did not attend'
Borooah et al.	2013	UK (Scotland)	May 2006-April 2007 (Traditional referrals) May 2008-April 2009 (COERU)	Quantitative prospective analysis of 8821 referrals made using a traditional referral pathway	To assess a centralised ophthalmic electronic referral unit (COERU)	All ocular conditions	Photographs	Waiting times reduced from a median of 14 weeks (0-32) with traditional referral to 4 weeks (0-12) with the COERU. No significant increase in no. of referrals (8821 vs 8707, $p=0.38$). Significantly less new patients seen face-to-face (8714 Vs 7462, $p<0.0001$) Significantly less unscheduled patients attending eye casualty (2671 Vs 1984, $p<0.0001$) Significantly less patients not attending scheduled appointments (645 Vs 503,

				and 8707 referred using an e-referral pathway				p<0.0001) The departmental complaint rate reduced from 7.5 to 3.5 per annum with none relating to the COERU. There were no reported adverse events.
Trikha et al.	2012	UK	_	Quantitative retrospective analysis of 100 general referrals,	To evaluate the Portsmouth glaucoma scheme, utilising virtual clinics.	Glaucoma	Optic disc images	76% of 100 general referrals were deemed suitable for the refinement scheme. Optic disc assessment was gradable from the photographs 71% of the time. 11% of referrals into virtual clinic were subsequently given an appointment in the HES glaucoma clinic. The positive predictive rate was 0.78 (95% CI 0.65–0.87).
Kelly et al.	2011	UK	June 2010-August 2011	Quantitative analysis of 50 e-referrals	To complete a service review of an e-referral system	Retinal pathology	Photographs	96% of cases reviewed by an ophthalmologist within the next calendar day 34% of cases did not require onward referral and were followed up in primary care optometry
Cameron et al.	2009	UK(Scotland)	July 2005-January 2007	Quantitative prospective analysis of 346 e-referrals into an e-referral system	To assess a pilot electronic referral system	All ocular conditions	Photographs	160/346 (73%) referrals had imaging attached. All of which were sufficient quality 60/346 (20%) of all referrals were for suspect macular disease 128/346 referrals deemed not to need hospital review of which there was 124/128 agreement at F2F appointment 3/114 patients contacted said they preferred F2F review over virtual but "the rest were extremely positive about the new referral pathway"
Hanson et al.	2008	Canada	1st June 2004- 31st May 2006	Quantitative, retrospective review of 171 patients (190 visits)	To report long-term results of a teleophthalmology triage service for optometry referrals.	Retinal pathology	Stereo fundus imaging	**Outcomes:** 7 patients (4.1%) were found to have no evidence of ocular pathology in either eye. The most common retinal abnormality identified was macular degeneration (123 eyes) and diabetic retinopathy (47 eyes). 82 patients (48%) did not require referral, whereas 89 patients (52.0%) were referred for clinical examination. 28 patients were referred back to the optometrist for follow-up **Image quality:** 53/76 (70%) of patients referred for clinical examination of suspect macular degeneration did not have photographs of sufficient quality to make a definitive diagnosis of the wet or dry form on their digital retinal examination **Patient travel:** There was a total travel savings of 24,413.99 km and 295.09 hours, and an average travel savings of 301.41 km and 3.64 hours, for those patients who could be assessed by teleophthalmology alone.

Supplementary Table 6: Summary of studies focusing on asynchronous teleophthalmology outcomes

Author(s)	Year	Location	Study Period	Referral Refinement	Asynchronous Review	Results
Ford et al.	2019	UK	January–October 2017	Glaucoma	Consultant virtually reviewed fundus photographs, visual fields and clinical information for all patients seen.	For cases where the optometrist's recommendation was changed, 7.6% required more urgent care, and 13% less. Numbers of patients discharged did not change.
Keenan et al.	2015	UK	1st April 2010-31st March 2013	Glaucoma	Fundus photographs and visual fields for each patient were sent via secure NHS email. Clinical information was uploaded.	Following virtual review, a further 5.7% (n= 99) patients were discharged. 3.6% of all patients (n= 62) who had been discharged following community OSI assessment were recalled to a consultant-led clinic.
Ratnarajan et al.	2015	UK	_	Glaucoma	Assessment of (non-stereoscopic) optic disc photographs of 34 patients discharged from a glaucoma referral refinement scheme.	On virtual review by a consultant ophthalmologist, 13/34 (38%) were suspicious of glaucoma and 21 (62%) normal. Virtual review by consultant gave a sensitivity of 80% and specificity of 69% compared to the clinic-based assessment. Virtual review by hospital optometrist gave a sensitivity of 80% and specificity of 97% compared to the clinic-based assessment.
Roberts et al.	2015	UK	February 2005-February 2009	Glaucoma	Consultant virtually reviewed fundus photographs, visual fields and clinical information for all patients seen by level 1 SOGs and patients requested to be reviewed by level 2 SOGs	971 (29.6%) were un-assessable mainly due to cataract or other media opacity. Level 2 SOGs had an 87.8% agreement/non-significant disagreement with the consultant. Level 1 SOGs had a 75.9% agreement/non-significant disagreement with the consultant.
Devarajan et al.	2011	UK	4-year period	Glaucoma	Consultant reviewed disc photographs and completed referral refinement forms for 100 discharged patients	98/100-disc images considered gradable 2/98 (2%) required follow up in the HES but neither were started on treatment False negative rate of 3-10%
Syam et al.	2010	UK	February 2005-March 2007	Glaucoma	Review of all patients by the project lead using disc photographs	360/2368 (15.2%) were unusable due to cataract Unusable visual fields were very small (0.5%) Significant disagreement between the project lead's appraisal and findings of the SOGs was observed in: optic nerve (11%), visual field (7%), diagnosis (12%), treatment (10%), and follow-up (17%)

Supplementary Table 7: Summary of studies focusing on glaucoma referral refinement schemes combined with asynchronous teleophthalmology.

Author(s)	Year	Location	Study Period	Study Design	Aim(s)	Condition	Intervention	Main Results
Stewart et al.	2022	USA	February 2016-April 2018	Prospective analysis of agreement	Study agreement between telemedicine and in-person examinations for diagnosing and managing patients.	Paediatric eye conditions	Synchronous teleophthalmology using Polycom video conferencing system Pivot head glasses, Topcon digital slit lamp with camera attachment and a Keeler Digital Wireless Indirect Ophthalmoscope	210 patients were examined. 94 were comprehensive (new referral) and 116 were consultation (seen previously by attending optometrist) examinations. No primary diagnoses were changed between the telemedicine and in-person examinations. 2 non-primary diagnoses were changes but no management plans. 78.4% (consultation group) and 55.3% (comprehensive group) warranted being seen by a paediatric ophthalmologist. The remaining patients either did not need to be seen at all or could have been seen by a qualified paediatric optometrist. In all examinations, the ophthalmologist was able to hear and see the patient and visualise areas of interest. 98.5% of parents felt comfortable with the quality of the telemedicine examination. 97.1% reported they would participate in another one in the future.
Ghazala et al.	2021	UK (Scotland)	Pre lockdown = 1st Match 2019-22nd March 2020 During lockdown = 23rd March 2020-30th April 2020	Retrospective, analysis using a convenience sample from 154 responses from a survey of ophthalmologists.	To compare the uptake and two outcomes (avoided escalations to secondary care and conditions where escalation was or was not avoided) of live teleophthalmology before and after COVID-19 lockdown.	All ocular conditions	Synchronous teleophthalmology using a video slit lamp or an iPad Air 2 with a bespoke mount.	134 calls were made pre-lockdown and 116 during-lockdown. 50/78 (64.1%) surveyed pre-lockdown said a referral to secondary care had been avoided versus 65/76 (85.5%) surveyed during-lockdown (p=0.001). Sub-speciality where escalation was avoided (n = 115) was predominantly anterior or posterior segment (n = 101). There were no differences in sub-speciality pre- and during lockdown: anterior segment 25/50 vs 35/65 (p = 0.34); posterior segment 16/ 50 vs 25/65 (p = 0.24). Lid, peri-orbital, neuro-ophthalmology and uveitis presentations formed a relatively greater proportion of cases where escalation was not avoided than the same conditions where escalation was avoided (n = 12/39 vs 14/115, p = 0.004)

Ghazala et al.	2021	UK (Scotland)	23rd March-16th June 2020	Survey of experience of 6 referrals	To share a method of appropriately connecting patients directly to tertiary ophthalmology centres where sub-specialist vitreoretinal (VR) surgical management is reduced.	VR referrals	Live teleophthalmology with a VR surgeon via a video or adapted slit lamp.	In 5/5 referrals for suspect RD, patients were listed directly for operation and avoided having to attend the local ophthalmology department. The mean Likert score for satisfaction with the teleophthalmology consultation was 5/5 from optometrists, ophthalmologists and patients. Optometrists, ophthalmologists and patients all gave a mean Likert score of 5/5 for likeliness to recommend this type of consultation to a friend, family member and/or colleague. Ophthalmologists gave a mean Likert score of 5/5 for sound quality, video quality and connection reliability. Optometrists gave a mean Likert score of 4.6/5 for sound quality, 4.6/5 for video quality and 5/5 connection reliability
Kanabar et al.	2021	UK	Primary care: 1st June-31st July 2020 Secondary care: 17th June-11th August 2020	Quantitative retrospective and prospective analysis of referrals.	The aim was to evaluate the COVID-19 urgent eye care service (CUES) for primary and secondary care activity.	Urgent referrals	Primary care optometry telephone triage and HES emergency hotline.	91.1-91.7% were initially deemed eligible for a telemedicine appointment.53.3-55.6% were given face-to-face appointments.13.0-14.3% of cases were provisionally referred to secondary care HES.Of the 101 provisional referrals to MREH from CUES received, 69 (68.3%) were accepted Of the 61 accepted referrals graded by the hospital clinicians, 39 (63.9%) were categorised as either being in ‘agreement’ or ‘partial agreement’. Of the 32 rejected referrals, 25 (78.1%) were rejected due to the condition not being deemed an emergency 420 telephone calls were recorded and signposted to either CUES, the MREH EED, or local hospitals/optometrist practices.
Moussa et al.	2020	UK	Pre-Intervention January-February 2020 Post-intervention April-July 2020	Quantitative retrospective audit of pre-intervention (n=2868) and post-intervention (n=4870) patient interactions	To examine the impact of a restructured ophthalmic referral at a tertiary referral centre.	All ocular conditions	Telephone triage service and a new on-call phone triage system. An NHS.net e-referral system for use by community optometrist	Pre-intervention, 1281(44.7%) patients required face-to-face follow up compared to 1192 (24.5%) post-intervention (p<0.0001) There was a higher proportion of discharges (p<0.0001), reduction in face-to-face visits (p<0.0001) and reduction in patients discharged without requiring face-to-face consultations (p<0.0001) post-intervention. Comparing face-to-face appointments only, there was no significant change in discharge rate (p=0.7245) July 2020 (relaxed lockdown rules) had significantly fewer face-to-face appointments (p<0.0001) and a higher overall discharge rate (p=0.0006) compared to pre-intervention.

Supplementary Table 8: Summary of studies focusing on synchronous teleophthalmology outcomes.

Appendix 2: Quantitative Study Supplementary Material

Clinical Case Selection

The 30 cases were chosen to cover a range of pathologies, as well as to include healthy scans. Cases were selected based on the AI model output in order to present the range of possible outcomes from the algorithm. When choosing cases, the diagnoses suggested by the AI were compared to the 'gold standard' diagnosis. The gold standard diagnosis was each patient's clinical diagnosis, which was decided on by an ophthalmologist during the patient's visit to MEH. This involved a thorough face to face with a full history and symptoms. For some patients, it also involved additional diagnostic tests. The following categories were used to select cases:

1. Normal (10% of cases) - For these cases, a normal, healthy OCT scan was displayed, which the AI classification algorithm correctly identified as normal.

2. Clear-cut (30% of cases) - For these cases, the diagnosis was 'clear-cut'. The cases clearly showed a diagnosis with no other suggestive findings of another diagnosis. Diagnostic clarity was clearly identified using the AI outputs and the segmentations.

3. False positive (10% of cases) - For these cases, the AI erroneously suggested an abnormality in a healthy retina.

4. Edge cases (30% of cases) - These were difficult, ambiguous cases. There may have been more than one possible diagnosis from the information given.

5. False negative (20% of cases) - For these cases, the AI result erroneously identified either a healthy retina from a scan with pathology present or a diagnosis that required routine/no referral when the ground truth was a diagnosis requiring urgent referral.

The cases were matched across the 3 types of presentation. For each set of 3 matched cases. The difficulty of the cases was matched through considering clinical information cues, OCT imaging and fundus image: i.e., how difficult each case would be to diagnose correctly without any AI support. The cases were purposely chosen to be difficult, thus included an artificially high number of situations where the AI was incorrect (false positives and negatives) or unsure (edge cases). The accuracy of the diagnosis algorithm was set to 70%. This was less than the true accuracy of 94.5% and was not revealed to the participants until debriefing. This study design choice was to enable a focus on interesting cases whereby incorrect AI may influence participants' decisions.

Participant Experience

Thirty qualified optometrists were recruited to the study, all of whom currently worked within the hospital eye service. No minimum number of years' experience was required but optometrists had to be fully qualified. Participants were divided into two groups, based on their level of experience in medical retina (MR) which was used as a surrogate for their familiarity of interpreting retinal OCT scans. The group allocation criteria are displayed in Supplementary Figure 1. If a participant was currently working in an MR clinic, and had been there for more than 1 year, they were allocated to the more experienced group. Others were allocated to the less experienced group, including those who had never worked in MR, who had not worked in MR in the past year, and those who had worked in MR for less than a year. This time period was decided with a consultant optometrist specialising in MR as most optometrists work in MR for only 1 or 2 sessions per week and require supervision for roughly the first 4-6 months. Also, without working in the clinic for over a year, OCT interpretation skills are likely to have degraded. It is acknowledged that this does not provide a distinct divide between more and less experienced groups, as optometrists may also have some knowledge of retinal OCT scans from outside MR clinics. However, these classification rules were chosen as a reasonable measure of level of experience.

Participant Training

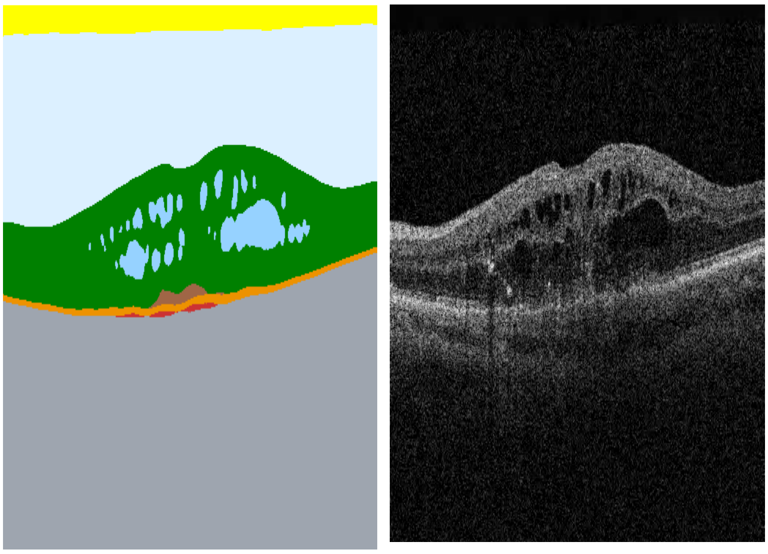
Clear instructions were provided for how to navigate through the survey and how to clearly view the OCT volume scans prior to any study cases being presented. Participants were shown an example of an AI segmentation map along with the diagnosis probability percentages. This example was annotated with each aspect clearly explained. If the participant indicated that they were still unclear about what the AI segmentation and outputs represented, they were unable to complete the study at that point and were encouraged to contact the study investigator. All 30 participants indicated that they understood what the AI displayed. No information was given about the algorithms' diagnostic accuracy.

Participant Training - Segmentation Overlays

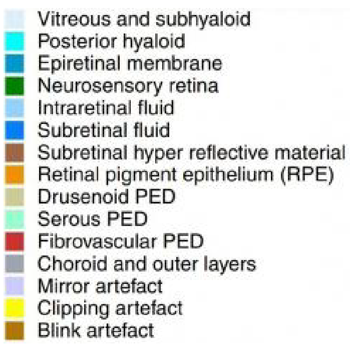
The following was shown to all participants during the training phase of the study:

You will also be provided with 'segmentation maps' produced using artificial intelligence (AI) algorithms. These maps display identified features within the OCT scan (for example intra-retinal fluid (IRF)). Segmentations are presented as overlays, covering the OCT scan. If a specific feature is identified, it is colour coded, based on a key that will be provided to you. An example can be seen below:

Example:



Key:



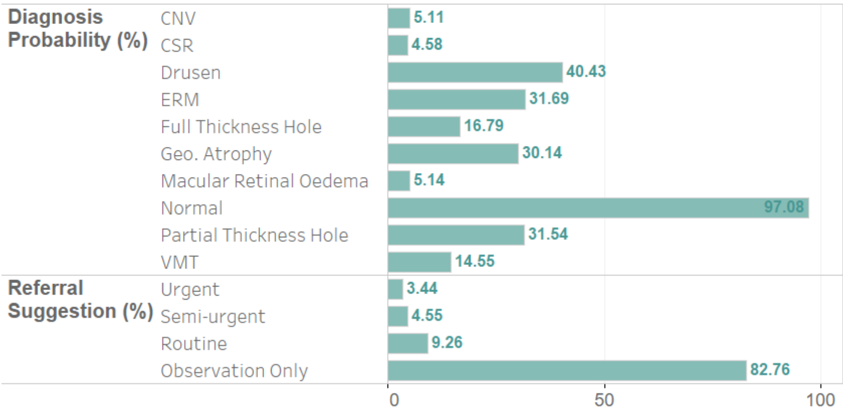
**(PED = Pigment epithelial detachment)

In this example, the segmentation has identified numerous large pockets of intra-retinal fluid. It has also identified a fibrovascular PED and sub-retinal hyper-reflective material. Other colour coded areas represent anatomical structures.

The results displayed in this segmentation map are then used by a separate AI algorithm to determine a suggested probable diagnosis.

Participant Training - AI Diagnostic Outputs The following was shown to all participants during the training phase of the study:

You will also be provided with bar charts, presenting the output from an algorithm designed to suggest the most probable diagnosis as well as a referral suggestion. This algorithm uses the results from the OCT segmentation maps to determine the most likely diagnosis or pathology present. The following image is an example of how this output will be presented:



Each percentage is out of 100 and is the algorithm's output probability of each diagnosis being present. This example demonstrates a 97.08% probability that the OCT scan is normal.

The percentage for each diagnosis can be between 0-100%. The presence of each condition is assessed independently of the other diagnoses.

The AI may not always be as confident in its diagnosis. For example, consider the AI predicted a diagnosis of CNV with a value of 55% probability, but at the same time also predicted the diagnosis was MRO with 55%. For the two conditions considered independently, the AI predicts the same probability that both are present.

Statistical Methods

As our data did not meet the ANOVA assumptions, we used non-parametric tests for analysis. In particular we used the Aligned Rank Transform (ART) for factorial data, to assess the presence of interactions between N number of different factors. ART relies on a pre-processing step that aligns data before applying averaged ranks. After this step, common ANOVA and post-hoc analysis can be performed. By carrying out the pre-processing step, ART can be used in circumstances similar to the parametric ANOVA, despite the dependent variable being continuous or ordinal and not normally distributed.

Supplementary Exploratory Analysis

After running the analysis reported in the paper, we noticed that three cases across the conditions (n=1 'no AI', n=1 'AI diagnosis' and n=1 'AI diagnosis + segmentation') were particularly ambiguous, as they were borderline epiretinal membrane. In order to assess whether our results for diagnostic accuracy and agreement with AI were significantly impacted by these three cases, we repeated the analysis excluding them. *Thus, for each of the three case presentation formats, 270 diagnostic responses were assessed.* An ANOVA with ART adjustment revealed significant differences in correct responses for the same factors as the original analysiss; there was a signficant difference across the three presentation formats ($p<0{\cdot}001$) (Supplementary Table 1). A significant effect of the order of case presentation was again found ($p=0{\cdot}007$). There was no significant effect of experience on the number of correct responses. When testing interactions between factors, a signficant interaction between order and presentation (‘no AI’, ‘AI diagnosis’, ‘AI diagnosis + segmentation) was found ($p=0{\cdot}006$). All other interactions showed no signficant effect.

	Diagnosis	
Factor(s)	**F-value**	**p-value**
1 Experience	1.256	0.266
2 Order	5.38	**0.007***
3 Presentation	10.86	**<0.001**
4 Experience: Order	1.056	0.353
5 Experience: Presentation	2.166	0.122
6 Order: Presentation	3.926	**0.006***
7 Experience:Order:Presentation	0.523	0.719

* p values considered statistically significant

Supplementary Table 9: Results from ANOVA testing on number of correct diagnoses. ANOVA performed on results post-analysis using aligned rank tranform (ART). Results for factors 1-3 represent the effect of a single factor on diagnosis. Results for factors 4-7 represent the effect of two or more factors interacting. Values in bold represent statistically significant results.

Effect of presentation

The participants’ responses were divided into 3 classes, based on the presentation of information. In the ‘no AI’ group, 213/270 (79%) responses were correct. In the ‘AI diagnosis' group, 196/270 (73%) were correct. In the 'AI diagnosis + segmentation' group, 181/270 (67%) were correct. Post-hoc testing with Bonferroni correction again revealed signficant differences in correct responses between 2 pairs: no AI vs AI diagnosis + segmentation (p<0·001) and AI diagnosis + segmentation vs AI diagnosis (p=0·025). However, the differences between the no AI and AI diagnosis pairs were no longer significant (p=0·174). This change from signficant to non-significant is likely due to the smaller sample size creating less statistical power, as the difference in correct responses between these two conditions changed by just one response in the new analysis.

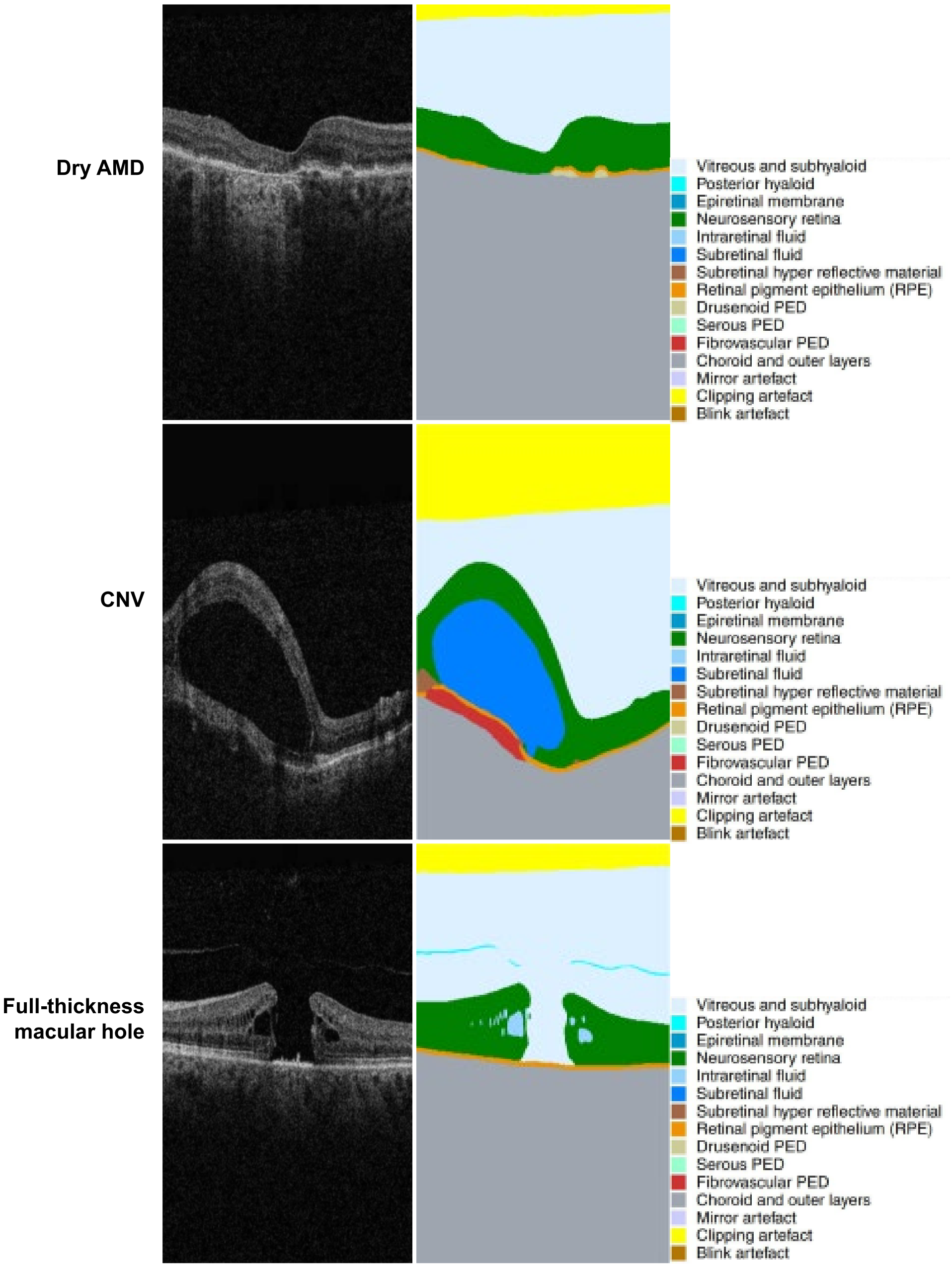
Participants' level of agreement with AI

We also assessed whether excluding the three cases affected the results for agreement with AI outputs with (AI diagnosis + segmentation) or without (AI diagnosis) segmentation overlays. The results again matched the original analysis whereby there was a significant effect of presentation format (p=0·006) (Supplementary Table 2) and no significant effect of experience (p=0·779) or order (p=0·822) or interactions effects.

	Diagnosis	
Factor(s)	**F-value**	**p-value**
1 Experience	0.08	0.779
2 Order	0.197	0.822
3 Presentation	8.15	**0.006***
4 Experience: Order	1.301	0.282
5 Experience: Presentation	0.883	0.352
6 Order: Presentation	0.195	0.824
7 Experience:Order:Presentation	0.407	0.668

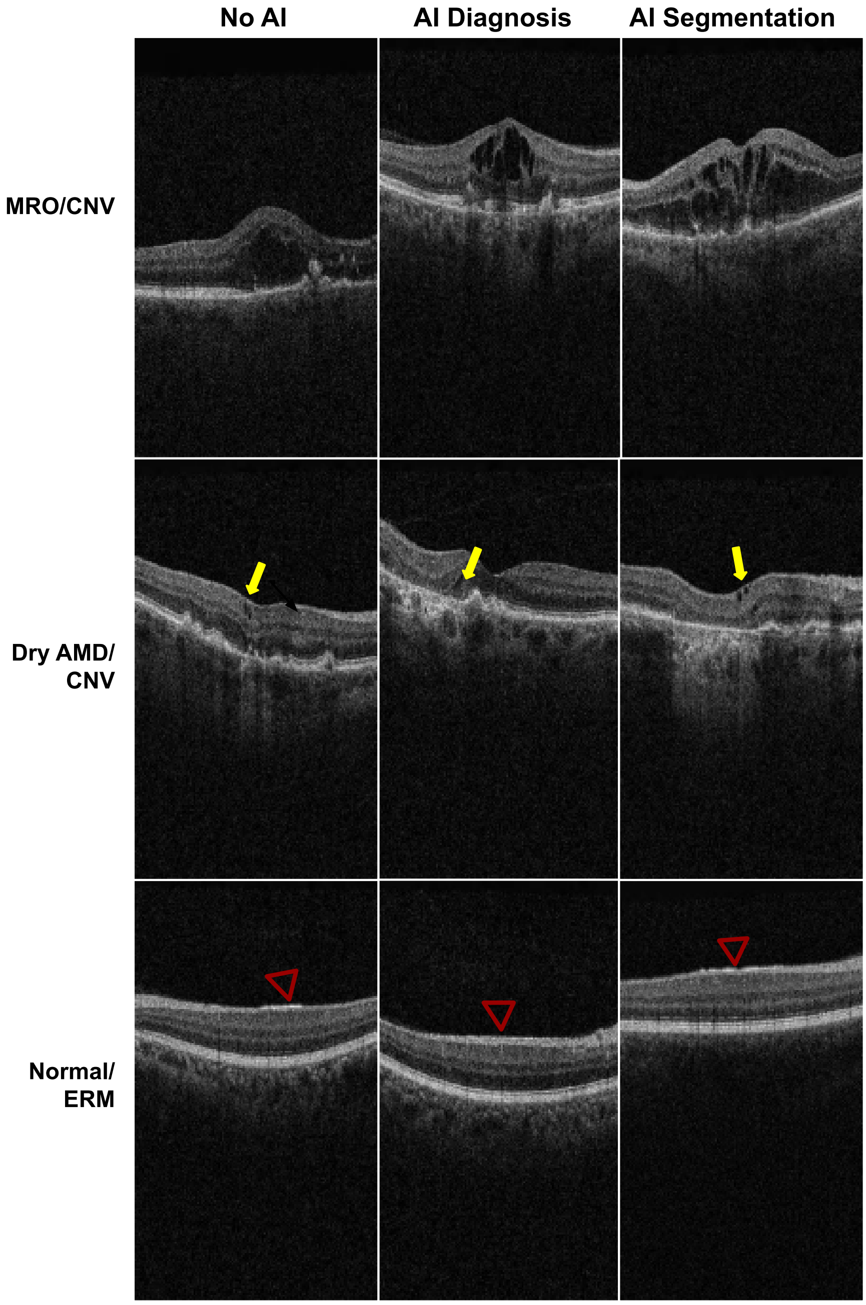
* p values considered statistically significant

Supplementary Table 10: Results from ANOVA testing on number of responses in agreement with AI outputs. ANOVA performed on results post-analysis using aligned rank tranform (ART). Results for factors 1-3 represent the effect of a single factor on agreement with AI. Results for factors 4-7 represent the effect of two or more factors interacting. Values in bold represent statistically significant results.

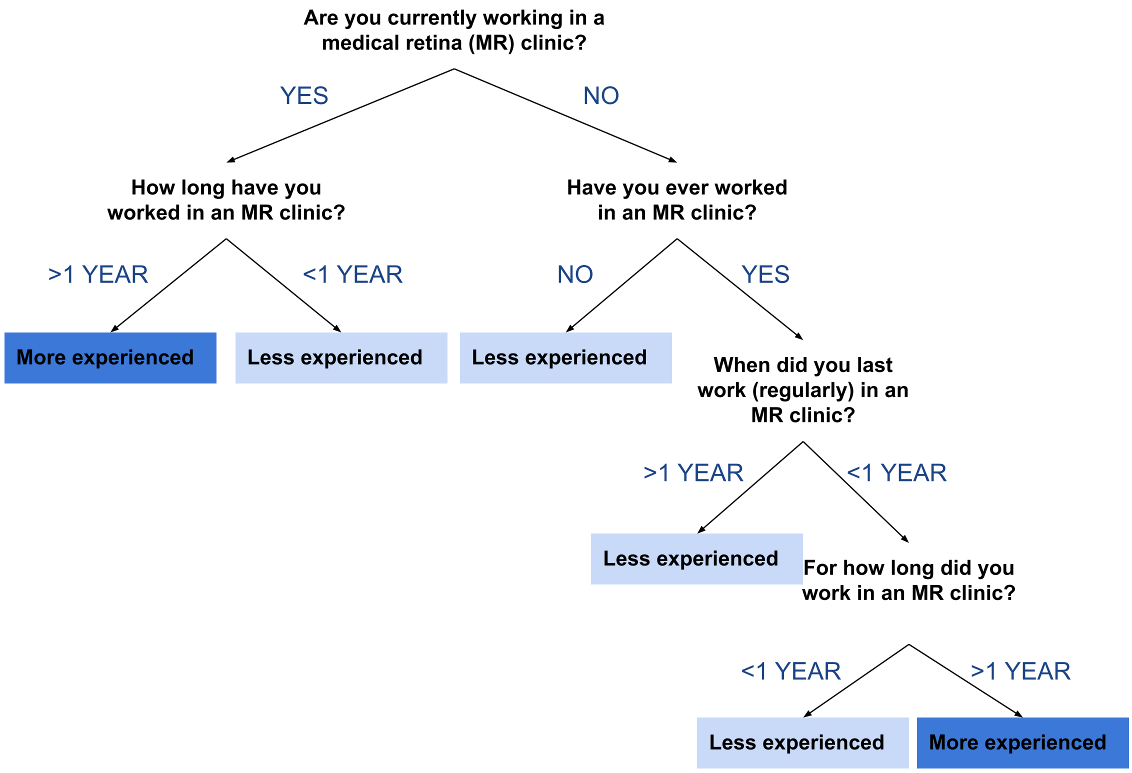


Supplementary Figure 1: Examples of OCT cases with corresponding segmentation overlays.

AMD = Age-related macular degeneration. CNV = choroidal neovascular membrane.



Supplementary Figure 2: Example of edge cases matched across the three conditions (arrows not displayed to participants but highlight regions of interest for the reader).



Supplementary Figure 3: The allocation to of participants to one of two groups based on experience of OCT interpretation.

MR = Medical Retina

Appendix 3: In Depth Interview Study Supplementary Material

Appendix 3.1 Information Sheet (displayed on REDCap)

Participant Information Sheet for Optometrists

UCL Research Ethics Committee Approval ID Number:
UCLIC_2022_008_ Blandford_Carmichael_Costanza

Title of Study:

PRIMARY CARE OPTOMETRISTS' CLINICAL DECISION SUPPORT NEEDS: A STUDY OF CURRENT INFORMATION SEEKING BEHAVIOURS AND EXPECTATIONS OF ARTIFICIAL INTELLIGENCE FOR SUPPORTING MANAGEMENT OF SUSPECTED RETINAL CONDITIONS.

Departments:

1. University College London Interaction Centre (UCLIC), London, United Kingdom
2. NIHR Biomedical Research Centre for Ophthalmology, Moorfields Eye Hospital NHS Foundation Trust and UCL Institute of Ophthalmology, London, UK

Name and Contact Details of the Researcher(s):

Josie Carmichael: josie.carmichael.20@ucl.ac.uk

Dilisha Patel: dilisha.patel@ucl.ac.uk

Professor Enrico Costanza: e.costanza@ucl.ac.uk

Professor Ann Blandford: a.blandford@ucl.ac.uk

Dr Konstantinos Balaskas: kbalaskas@nhs.net

Name and Contact Details of the Principal Researcher:

Professor Ann Blandford: a.blandford@ucl.ac.uk

Invitation Paragraph

You are being invited to take part in a research project for a PhD programme through University College London (UCL) and Moorfields Eye Hospital. Before you decide if you wish to take part, it is important for you to understand why the research is being done and what participation will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or if you would like more information and take time to decide whether you wish to take part. Thank you for reading this information.

What is the project's purpose?

In recent years, there has been widespread introduction of OCT and other advanced imaging in primary care optometric practice. It is not uncommon for optometrists to encounter challenging clinical cases and to seek advice and support from a range of sources when making clinical decisions. This may include contact with their peers and/or links to specialised professionals. Artificial intelligence (AI) offers a potential solution to the shortcomings of current clinical decision support available to optometrists. AI algorithms have demonstrated impressive performance across a range of ophthalmic applications, including the diagnosis of retinal conditions using OCT images. Therefore, AI may in the future be used as a clinical decision support system (CDSS) for optometrists making management decisions in primary care.

We aim to better understand optometrists' information needs in relation to challenging clinical cases with a focus on suspected retinal disease in order to inform the design and/or implementation of a new AI CDSS in primary care.

The main objectives of this study are:
1. To explore optometrists' experiences with OCT and other advanced imaging in primary care practice.
2. To explore if and where optometrists seek information when encountering 'challenging' clinical cases and how often these occur, with an emphasis on retinal conditions.
3. To explore why optometrists use their chosen source(s) of clinical support/information over other forms of support.
4. To explore optometrists' opinions on the future of AI support tools for diagnosing retinal conditions
5. To determine what information optometrists would ideally like to have from a clinical decision support tool, with a focus on an example for retinal conditions.

Why have I been chosen?
You have been invited to participate because you are:
- A qualified optometrist with an active general optical council (GOC) registration.
- Working mainly in primary care practice (more than 50% of your working time).
- Working in a primary care practice that offers OCT retinal imaging to patients.
- Able to communicate effectively in English, and do not consider yourself to be a vulnerable adult.
- Able to give informed consent.

We are aiming for **20-30 participants** to take part in the study.

Do I have to take part?

It is your decision whether to take part in the study. If you do decide to take part, you will be asked to sign a consent form. You can withdraw at any point during the study OR within 24 hours of taking part, without giving a reason. If you decide to withdraw you will be asked what you wish to happen to the data you have provided up until the point of withdrawal.

What will happen to me if I take part?

After signing an online consent form, you will be contacted to schedule an online meeting. The online meeting will take around 45-60 minutes and will involve an interview around your personal experiences in primary care practice, with an emphasis on patients with suspected retinal conditions.

The interview will also involve a demonstration of an AI system designed for the analysis of retinal OCT scans. You will be interviewed only once. The interview will be audio-recorded and transcribed. Screen recordings of your interaction with examples of clinical cases will also be used, however these will not include videos or images of you. No identifiable information will be included in the transcripts.

Will I be recorded and how will the recorded media be used?

The audio and screen recordings of your activities made during this research will be used only for analysis and for illustration in academic papers, conference presentations and/or lectures. No other use will be made of them without your written permission, and no one outside the project will be allowed access to the original recordings. The original recordings will be stored on a password protected USB drive and will be destroyed at the end of JC's PhD programme.

What are the possible disadvantages and risks of taking part?

No disadvantages or risks of taking part have been identified. In the unlikely event that participating causes you any distress, you are free to withdraw and to discuss concerns with the researchers.

What are the possible benefits of taking part?

You will be offered an Amazon voucher worth £50 to reimburse you for your time. We also hope that taking part will help you to reflect on how you diagnose and manage ocular conditions and where you currently seek clinical support. We may also share our findings with developers of clinical decision support systems in this space so that they may help to inform future research and/or design.

What if something goes wrong?

If you have any concerns with the conduct of this study, please raise them in the first instance with Professor Ann Blandford (a.blandford@ucl.ac.uk). If your concerns are not addressed to your satisfaction, then you may contact the Chair of the UCL Research Ethics Committee
- ethics@ucl.ac.uk

Will my taking part in this project be kept confidential?

All the information that we collect about you during the course of the research will be kept confidential. You will not be identifiable in any ensuing reports or publications.

Limits to confidentiality

Please note that assurances on confidentiality will be strictly adhered unless there are compelling and legitimate reasons for this to be breached. If this was the case, we would inform you of any decisions that might limit your confidentiality.

What will happen to the results of the research project?

This study is part of JC's PhD project, and the findings will be reported as part of a PhD Thesis. Depending on the findings, the researchers may also publish the results in a journal or conference paper. Pseudonymised data will be stored securely for five years and may be reviewed in subsequent studies that have a related focus.

Local Data Protection Privacy Notice:

The controller for this project will be University College London (UCL). The UCL Data Protection Officer provides oversight of UCL activities involving the processing of personal data and can be contacted at data-protection@ucl.ac.uk The only personal information retained will be your chosen contact details if you wish to be informed of the outcome of this study. These will be held securely and separately from the pseudonymised data that you provide for the study. Further information on how UCL uses participant information in Health and Care Research Studies can be found at:

UCL General Privacy Notice for Participants and Researchers in Health and Care Research Studies | Legal Services - UCL - University College London. The information required to be provided to participants under data protection legislation (GDPR and DPA 2018) is given across both the 'local' and 'general' privacy notices.

The categories of personal data used will be as follows:

- Name
- Email address

The lawful basis that would be used to process your personal data will be 'performance of a task in the public interest'. Your personal data will be processed so long as it is required for the research project. We will pseudonymise the personal data you provide and will endeavour to minimise the processing of personal data wherever possible.

If you are concerned about how your personal data is being processed, or if you would like to contact us about your rights, please contact UCL in the first instance at data-protection@ucl.ac.uk.

Who is organising and funding the research?

The NIHR Biomedical Research Centre at Moorfields Eye Hospital NHS Foundation Trust and the Engineering and Physical Sciences Research Council **(EPSRC)** co-fund JC's PhD studentship within the University College London (UCL) i4Health Centre for Doctoral Training.

Contact for further information:

If you require further information about this study and/or the information provided in this document, please contact Professor Ann Blandford at UCL (a.blandford@ucl.ac.uk). Alternatively, you may contact Dr Konstantinos at Moorfields Eye Hospital (kbalaskas@nhs.net).

You may keep a copy of this information sheet as well as a copy of your signed consent form if deciding to participate in the study.

Thank you for reading this information sheet and for considering taking part in this research study.

Appendix 3.2 Consent Form (Displayed on REDCap)

CONSENT FORM FOR *OPTOMETRISTS* IN RESEARCH STUDIES

Please complete this form after you have read the Information Sheet and/or listened to an explanation about the research.

Title of Study:

PRIMARY CARE OPTOMETRISTS' CLINICAL DECISION SUPPORT NEEDS: A STUDY OF CURRENT INFORMATION SEEKING BEHAVIOURS AND EXPECTATIONS OF ARTIFICIAL INTELLIGENCE FOR SUPPORTING MANAGEMENT OF SUSPECTED RETINAL CONDITIONS.

Departments:

1.University College London Interaction Centre (UCLIC), London, United Kingdom
2. NIHR Biomedical Research Centre for Ophthalmology, Moorfields Eye Hospital NHS Foundation Trust and UCL Institute of Ophthalmology, London, UK

Name and Contact Details of the Researcher(s):

Josie Carmichael: josie.carmichael.20@ucl.ac.uk

Dilisha Patel: dilisha.patel@ucl.ac.uk

Professor Enrico Costanza: e.costanza@ucl.ac.uk

Professor Ann Blandford: a.blandford@ucl.ac.uk

Dr Konstantinos Balaskas: kbalaskas@nhs.net

Name and Contact Details of the Principal Researcher:

Professor Ann Blandford: a.blandford@ucl.ac.uk

Thank you for considering taking part in this research. The person organising the research must explain the project to you before you agree to take part. If you have any questions arising from the Information Sheet or explanation already given to you, please ask the researcher before you decide whether to join in. You will be given a copy of this Consent Form to keep and refer to at any time.

I confirm that I understand that by ticking/initialling each box below I am consenting to this element of the study. I understand that it will be assumed that unticked/initialled boxes means that I DO NOT consent to that part of the study. I understand that by not giving consent for some elements that I may be deemed ineligible for the study.

1)	I confirm that I have read and understood the Information Sheet for the above study. I have had an opportunity to consider the information and what will be expected of me. I have also had the opportunity to ask questions which have been answered to my satisfaction and would like to take part in an individual online interview.
2)	I understand that I will be able to withdraw my data up to 24 hours after my interview.
3)	I consent to participate in the study. I understand that my personal information *(name and email address)* will be used for the purposes explained to me. I understand that according to data protection legislation, 'public task' will be the lawful basis for processing.
4)	I understand that all personal information will remain confidential and that all efforts will be made to ensure I cannot be identified subject to legal constraints and professional guidelines. I understand that my data gathered in this study will be stored securely. It will not be possible to identify me in any publication.
5)	I understand that my information may be subject to review by responsible individuals from the University and/or funders for monitoring and audit purposes.
6)	I understand that my participation is voluntary and that I am free to withdraw at any time <u>during the interview OR with 24 hours post-interview,</u> without giving a reason, and without my legal rights being affected. I understand that if I decide to withdraw, any personal data I have provided up to that point will be deleted unless I agree otherwise.

7) I understand the potential risks of participating and the support that will be available to me should I become distressed during the course of the research.

8) I understand that I will be offered Amazon vouchers of £50 in value in reparation for my time as a guarantee of benefit that has been made to encourage me to participate.

9) I understand that the data will not be made available to any commercial organisations but is solely the responsibility of the researcher(s) undertaking this study.

10) I agree that my pseudonymised research data may be used by others for future research. [No one will be able to identify you when this data is shared].

11) I understand that the information I have submitted will be published as a report and I will inform the researcher if I wish to receive a copy of it.

12) I consent to my interview being audio/video recorded and understand that the recordings will be securely stored and destroyed at the end of Josie Carmichael's PhD programme.

13) I confirm that I will not produce any of my own video or audio recordings of the interview and I will not capture and keep any information presented during the demonstration phase of the interview.

14) I confirm that I understand the inclusion criteria as detailed in the Information Sheet and explained to me by the researcher; and I fall under the inclusion criteria.

15) I have informed the researcher of any other research in which I am currently involved or have been involved in during the past 12 months.

16) I am aware of who I should contact if I wish to lodge a complaint.

17) I voluntarily agree to take part in this study.

18) I understand that other authenticated researchers will have access to my pseudonymised data.

19) I would like my contact details to be retained so that I can be contacted in the future by UCL researchers who would like to invite you to participate in follow up studies to this project, or in future studies of a similar nature.

20) **Participant Name**

21) **Signature (optional)** Ac

22) **GOC number**

23) **Participant Email**

Appendix 3.3 Topic Guide

Stage 1: Introduction to research

Introduce yourself, the research topic and what the interview will entail. Confirm consent and right to withdraw. Confirm that the participant consents to being audio and screen recorded and that they will not make any of their own recordings/images during the interview. Remind them to keep any patients/colleagues, that they may discuss, anonymous.

Stage 2: Background information

"Tell me about your professional background:"

Further questions to make sure points are covered:

- How long have you been qualified?
- Do you work in community practice full time? If not, what other work do you do?
- Do you mainly work in a multiple or independent community practice?
- Do you have any specialist interests and/or further qualifications?
- How many clinics running at once?

Stage 3: *OCT interpretation and use in clinical workflows*

Confirm OCT is used regularly in primary care practice.

"Can you talk me through how OCT imaging would be used during typical patient appointment? When would you choose to use this imaging and where does it fit into the patient appointment journey?"

Further questions to make sure points are covered:

- Are results always discussed with patients? What may affect this?
- If done first does is shape the eye exam?
- Which tasks related to OCT imaging (if any) get delegated to colleagues?
- What training have you received to interpret these images? Was it one-off/ongoing? Who has provided it?
- Do you feel that the training and experience you have had is sufficient for you to interpret these scans independently?

Stage 4: Information Seeking for memorable cases

"These next questions relate to your experience of clinical cases you have personally found challenging. I would like you to think of a memorable case or cases, encountered in primary care, that required you to seek further information to make a diagnostic and/or management decision. This could be a case or cases that stand out the most in your memory or simply the most recent for which you sought information. Can you tell me a bit about this case or cases as well as how and where you sought additional support? Please remember to keep patients anonymous"

Further questions to make sure points are covered:

- What information did you need to know that wasn't immediately available to you? How did you decide where to seek the information and what factors affected you using this source? Were you able to access the desired information from one source or did you have to approach multiple sources and how long did it take?

- What were the benefits in your opinion of the information source(s) used?
- What were the disadvantages in your opinion of the information source(s) used?
- Are you a member of any groups or forums where clinical cases are discussed? Can you tell me a bit about the group(s)?
- Does your employer offer any groups or forums you can access for this purpose? Do you use them? If not, why?
- How often would say you encounter a clinical case where you need to seek further advice when managing the patient.

Stage 5: Assessing difficult cases of suspected retinal disease.

"For the next part of the interview, I am going to show you three clinical cases that include retinal OCT imaging. For each, I would like to assess the case and to 'think-aloud' when doing so. By think-aloud, I mean describe what you are assessing, your thoughts on the clinical findings, your tentative diagnosis and how you would manage this patient in primary care. Please note that we are not assessing your diagnostic performance, these cases have purposely been chosen as ambiguous cases, by which I mean the diagnosis is open to interpretation. Your arrow keys can be used to scroll through the oct scan"

- Do you feel like you have enough information to diagnose and manage this patient independently?
- What other information would be useful to you when managing this patient and where would you seek this information?

Stage 6: potential for AI use in primary care

"For the last part of the interview, I would like to discuss the potential for artificial intelligence technologies to be used in primary care, to help optometrists in making clinical decisions and show you some examples. But firstly, I would like to hear what you think an AI decision support system is from your perspective? What, if anything, do you know about them? There are no right or wrong answers"

Further questions to make sure points are covered:

- Our system -- Do you think an AI system would fit better as a tool to be used by optometrists or to work independently? Why?
- What sort of primary care tasks do you think it may help with?

"I'm now going to show you the three clinical cases you assessed earlier, but this time additionally presented with outputs from AI technology that has been developed to help with the interpretation of OCT scans. I'll firstly give an overview of the example AI system. Please note that although this system has been trained on thousands of images and its accuracy validated, the method we are using to present its outputs to you has not. We are simply using this as an example for you.

The example system uses two separate sets of algorithms. The first set of algorithms uses the OCT scan as an input and segments the OCT scan into *identified features of both retinal anatomy and areas of pathology (for example intra-retinal fluid (IRF)). Segmentations are presented as overlays,* *covering the OCT scan. If a specific feature is identified, it is colour coded, based on a key. An example of a normal scan with no pathology identified can be seen here.*

The results displayed in this segmentation map are then used by a second set of algorithms to determine if it detects a number of different diagnoses being present. Of course some of these diagnoses can be present at the same time. The algorithm also considers four management different suggestions. i,e, should the patient be referred or not, and if so how urgently? It gives its prediction of the management suggestion based on probabilities out of 100%. We are using bar charts to represent these probabilities. The results for the four management options add up to 100%, so whichever options has the highest percentage is the AI's most probable suggestion for management.

This second case demonstrates an example of the AI's outputs when pathology has been detected. Do you have any questions about the system at this point?

Questions covered for each of the three cases:

- What are your thoughts on the information given? What do you think are the positives and negatives?"
- Would you find this information helpful in primary care for diagnosing and managing the patient?
- What information is most important to you? Anatomic features highlighted vs diagnosis vs referral (and urgency) vs combination of two or more?
- With this additional information from the AI, would you change your diagnosis and management of X, made without AI support?

Diagnostic outputs

- Is it clear from the diagnostic probabilities what the AI is predicting?
- What are your opinions around displaying all of the possible diagnoses with their probabilities vs just displaying the ones that are present?

Segmentation Overlays

- What is your opinion on the segmentation overlays? Do they think they are useful?
- Are the overlays easy to interpret in your opinion?
- Would there be other ways of highlighted clinical features which you would prefer?

Is there any other information you would like from a system like this?
Would this be better presented alongside as in our study or after the optometrist has assessed the case themself.

Stage 7: close the interview

"We've now come to the end of the interview. Are there any other thoughts or opinions you would like to share? Are there any other points you would like to mentions"

"Thank you again for taking part. We appreciate your participation"

Appendix 3.4 Individual Participant Responses to AI System

Optimistic and Neutral Participants

Participant 1 was very enthusiastic about the potential of AI in optometry even before seeing the demonstration. When first presented with the AI system, they expressed immediate acceptance, stating they "loved it" without delving deeply into the outputs. Their enthusiasm was partly driven by their self-professed lack of confidence in their ability to interpret OCT scans, which led them to inherently trust the AI’s suggested diagnoses, even when they pointed out that the AI missed certain areas of interest.

Participant 2 also held very positive views on AI’s potential to assist in decision-making. Throughout the demonstrations, they did not express any doubt about the AI's accuracy, even when its management suggestions differed from their own. They allowed the AI’s outputs to strongly influence their re-assessment of clinical cases, indicating a high level of trust in the AI’s capabilities.

Participant 4 Participant 4 responded positively about AI prior to and during the AI demonstration. They found the segmentation maps particularly helpful and said the AI outputs reassured them when they were uncertain, influencing them to change their management decisions in some cases. They welcomed the AI’s input but emphasised that they would still ultimately rely on their own judgment, particularly when output suggestion percentages were close.

Participant 5 Participant 5 was neutral about AI and accepted its outputs without much scepticism. They found the segmentation maps the most useful, especially when image quality was poor, and saw the AI as a helpful ‘backup’ for confirming their thoughts. While they didn’t strongly challenge the outputs, They also didn’t fully rely on them, expressing that more experience would be needed to build trust. The AI did influence their confidence in their own assessment, particularly case 3, where they said the outputs made them feel “more comfortable” with their management decision.

Participant 7 was optimistic about AI’s role in optometry, particularly in primary care. Their positive outlook led them to automatically align with the AI’s outputs during the demonstrations, stating that they began to "agree" with the system's suggestions as soon as they viewed them.

Participant 8 viewed AI as a valuable tool, particularly for less experienced optometrists. Although they disagreed with the AI’s specific suggestions in some cases, they still acknowledged the AI's usefulness. For instance, they disagreed with the AI's interpretation of a fibrovascular PED in an example segmentation map, but still found the segmentation helpful and was overall positive about the AI’s contributions.

Participant 14 was neutral towards AI and had no prior experience of it in healthcare. They responded positively to the segmentation maps, finding them clear and helpful, but was less convinced by the diagnostic and management outputs. Although they didn’t change their clinical decisions based on the AI, they admitted it made them doubt themself and rethink their assessment of the cases. Where the AI agreed with them it boosted their confidence.

Participant 15 was knowledgeable about AI and generally positive about its potential. Despite occasionally disagreeing with the AI system during the demonstration, they remained supportive of its use, particularly as a tool to aid less-experienced optometrists. They mentioned that the AI’s outputs made them reconsider their initial decisions, although they did not ultimately change the original assessments.

Participant 17 was initially neutral about AI, with limited prior knowledge of its role in optometry. They were influenced by the AI outputs during the demonstration, particularly in case 3 where they changed their referral decision based on the AI’s suggestions. They found the segmentation maps helpful in one case and saw potential for the system to support decision-making.

Participant 18 was open to AI solutions, especially those that support optometrists rather than replace them. Their initial positivity towards AI made them more accepting of the AI’s segmentation maps, even when they had reservations about its accuracy. They allowed the AI’s outputs to influence their management decisions when they were unsure about their initial assessment, demonstrating a cautious but accepting approach.

Participant 19 was very positive about AI and enthusiastic about its potential to improve optometric practice. They found the segmentation maps particularly helpful for simplifying complex scans and confirming his interpretations. The AI outputs reassured them and influenced how they thought about the cases, even when they didn't change their management. They felt the system already performed at a high level and was excited about its practical value.

Participant 20 also held a positive view of AI, considering that it could be a useful tool to help optometrists confirm their interpretations. They appreciated the AI's ability to "confirm what you already know" and did not question the AI's outputs.

Sceptical Participants

The participants who were initially sceptical of AI (n=8) remained critical throughout their interactions with the AI system. This scepticism manifested in their tendency to reject AI's suggestions, particularly when these suggestions contradicted their own assessments. Even when the AI's outputs aligned with their judgments, these participants often felt that the AI did not add value, as it failed to provide additional or useful information. Their scepticism was rooted in concerns about AI's accuracy, reliability, and the potential to undermine clinical skills beyond their existing knowledge.

Participant 3 was critical of AI from the outset, expressing the belief that "*a person is always going to be more accurate*." When presented with AI outputs that contradicted their initial assessment, they assumed that the AI was incorrect and dismissed its suggestions. Their scepticism appeared grounded in a fundamental distrust of AI's ability to match the accuracy of human clinicians.

Participant 6 was sceptical of AI before being shown the system's outputs. They questioned the level of "intelligence" AI could offer and expressed a desire for more detailed information about its reliability and accuracy. Their scepticism carried over into their interactions with the AI system. When the AI's segmentation map matched their assessment, they did not see the AI as a useful tool. Conversely, when the AI disagreed with their assessment, they did not trust its interpretation, further reinforcing their scepticism.

Participant 9 expressed doubts about AI's usefulness in specific clinical scenarios, such as distinguishing between wet and dry macular degeneration. They believed that AI should be clinician-driven and was concerned that relying too heavily on AI could erode clinical skills. While they did not automatically assume the AI was wrong, they remained critical of its outputs.

Participant 10 was sceptical about the practical application of AI in clinical practice. Therefore, even when the AI's suggestions aligned with their clinical judgment, they felt that the AI did not enhance their certainty or provide additional valuable insights. For instance, in Case 3, when the AI confirmed his diagnosis, they found it unhelpful because it did not offer any new information. They questioned the AI's methodology and sought more information on how it arrived at its conclusions, reflecting their overall scepticism about the AI's utility in everyday practice.

Participant 11 expressed concerns about AI's potential to miss critical issues, particularly those requiring urgent attention, which could result in delays and harm to patients. Their lack of trust in AI stemmed from their inexperience with the technology and the fear that it might be relied upon too heavily. Consequently, they did not find AI useful in the example cases, as it did not offer them any additional insights beyond what they already knew.

Participant 12 held a cautious and slightly sceptical view of AI. They appreciated the reassurance the segmentation maps provided and said the maps helped them notice features they may have otherwise missed. However, they remained doubtful of some diagnoses and was critical of the generalised management suggestions. Overall, they remained wary of relying on AI and was not influenced by outputs that were not aligned with their initial case assessment.

Participant 13 had a mixed opinion about AI. While they believed that optometrists should embrace new technology, they remained sceptical about AI's implementation and its influence on other practitioners. Although they were not personally swayed by AI outputs that contradicted his initial assessment, they recognised that other optometrists might be influenced by AI, which added to their concerns about its broader impact on the profession.

Participant 16 was sceptical of AI before being introduced to the example system, expressing doubts about its ability to "get everything exactly right." After reviewing the AI system, they remained unconvinced of its utility, particularly when it did not offer any information beyond what they already knew. Their scepticism was based on a belief that AI might not consistently deliver accurate or valuable insights.