DOES THE CONTENT OF SYMPTOMS AND HISTORY TAUGHT AT ASTON UNIVERSITY REFLECT THE HABITS OF OPTOMETRISTS WORKING IN MULTIPLE PRACTICE?

PETER GRAHAM HAMPSON

Doctor of Optometry

ASTON UNIVERSITY

March 2016

"Data is a precious thing and will last longer than the systems themselves"

Tim Berners-Lee

Aston University

Does the content of symptoms and history taught at Aston University reflect the habits of optometrists working in multiple practice?

Peter Graham Hampson

Doctor of Optometry, March 2016

Abstract

The purpose of this study was to determine whether Aston University's undergraduate classes on the symptoms and history element of eye examinations reflected the habits of optometrists working in multiple practice, the destination of most optometry graduates.

Data abstraction was carried out on a single free text field within electronic eye examination records taken from a major community multiple practice. Company policy required optometrists to enter symptoms and history in this field.

The feasibility of carrying out Bayesian searches on free text fields was investigated. Electronic searches were carried out to identify 163 text items linked to 11 classes of presenting symptoms in 51,944 records. Likelihood ratios were calculated for all text item/presenting symptom combinations in a training dataset of 1075 manually classified records. These likelihood ratios were applied to naïve Bayesian searches for presenting symptoms in the training dataset. Post-test probability threshold values were adjusted to match known and estimated prevalence for each symptom presentation type. These adjusted threshold values resulted in diagnostic accuracy of between 83 and 99% (depending on the presenting symptom class). The same likelihood ratios and adjusted threshold values were applied to larger scale naïve Bayesian searches in order to estimate the prevalence of each presenting symptom class in all 51,944 records. This part of the study showed that similar Bayesian searches on the more complex and numerous elements of complete symptoms and history free text fields would not have been feasible.

This being the case, detailed manual searches through 224 free text fields to determine how often optometrists asked 105 symptom and history test items taught at Aston University. Asking rates varied from 0 to 88%. The proportion of expected questions asked in individual records (conformity) tended to be higher for eye examinations that were routine (no presenting symptoms: 95% confidence limits 41 to 51%) compared to those with presenting symptoms (the means for which ranged from 25 to 34%). Optometrists tended to ask database-style questions (mean asking rates varied from 33 to 40% depending on the presenting symptom) more often than problem-orientated style questions (mean asking rates varied from 22 to 33% depending on the presenting symptoms). Decision tree analyses were used to explore the data in more depth and showed statistically significant regional variations in conformity.

In summary, typical practice did not reflect what was taught at Aston University. Optometrists tended not to vary the questions asked according to the presenting symptoms. It was anticipated that these findings would be of interest to optometry schools and members of legal teams involved with fitness to practice disputes.

Dedication

To my wife, who has supported me through all of the chaos.

Thank you.

Acknowledgements

I would like to note my sincere thanks to Dr Mark Dunne, my supervisor, for his knowledge guidance and support. It would not have been possible to navigate the various twists and turns that this project has thrown at me without his dedication.

Thanks to Dr Richard Armstrong for guidance on statistical matters.

Thanks once more to my wife and fellow optometrist for allowing me the time and support to complete this piece of work.

Contents

Chapter 2: Estimated prevalence of presentation types

Chapter 3: Estimation of the content of symptoms and history items recorded by optometrists in multiple-practice

Chapter 4: Summary and recommendations for further research

List of Figures

List of Tables

Abbreviations

ANOVA Analysis of Variance

CHAID Chi-square Automatic Interaction Detector

GOC General Optical Council

LEE Last Eye Examination

LME Last Medical Examination

LOFTSEA Location or Laterality, Onset, Frequency, and occurrence, Type and severity, Self-treatment, Effect on patient, Associated or secondary symptoms)

MEKA Multi-label extension to WEKA

MIPCA Migraine in Primary Care Advisors

MG Myasthenia Gravis

NUTS Nomenclature of Units for Territorial Statistics

POAG Primary Open Angle Glaucoma

PSA Prostate specific antigen

RFV Reason For a Visit

SOAP Subjective, Objective Analysis and Plan

TA Temporal arteritis

VDU Visual Display Unit

WEKA Waikito Environment for Knowledge Analysis

WOPEC Wales Optometric Post Graduate Education Centre

Chapter 1: Background

1.1: Introduction

This chapter lays out the research objectives of this study and discusses how students are taught to take a history and symptoms at Aston University. It goes on to look at what practitioners actually record and the challenges faced with extracting that information from within records. It will discuss methods that can be used to extract the data and the various limitations of these methods.

Research Objectives

The primary purpose of the study described in this thesis was to determine whether Aston University's undergraduate lectures on the symptoms and history element of eye examinations reflected the habits of optometrists working in multiple-practice. It should be noted that the majority of optometry graduates will work in these types of practice on graduation. This had never been investigated before and had the potential to (1) inform the profession about what is typical practice and (2) allow teachers to translate the study findings to teaching practice with a view to better preparing optometry students for a lifetime of work in multiple-practice.

An opportunity arose for a study of symptoms and history records from a very large set of eye examinations carried out across the United Kingdom during the month of August 2014. This data came in the form of clinical notes typed into a single "free text" box within a computerised optometric recording system used by one of the largest multiple-practice optical companies in the United Kingdom. This data had the potential to provide an accurate estimate of what a typical optometrist would record in this part of the eye examination.

The Association of Optometrists legal services team.

At the time of writing this thesis, the author was a practising optometrist who was also a director of the Association of Optometrists and part time clinical adviser to the Association of Optometrists Legal Services Team. He was also module leader at the Wales Optometric Post Graduate Education Centre (WOPEC) on the Legal Aspects of UK Optometry module.

Over the last 10 years the profession of optometry has become increasingly exposed to the litigious nature of the general public, with more claims being made against optometrists year on year. The number of claims is commercially sensitive but the Association of Optometrists opened 3,150 new case files in 2014 across all areas of optometry. This number does not include cases reported to other insurers.

The General Optical Council (GOC) reported an increase in the number of complaints from 148 in 2010-2011 to 189 in 2013-2014. This was against a background of an increase in the number of registrants. The percentage of complaints to the GOC is increasing, but it should be remembered that not all GOC complaints are capable of being pursued for damages and vice versa, that not all civil claims result in a complaint to the GOC.

Year	Number of complaints	% increase to previous year	Total number of registrants	% increase to previous year
2010-11	148	NA	24,656	NA
2011-12	149	0.68%	25,461	3.26%
2012-13	171	14.77%	26,616	4.54%
2013-14	189	10.53%	26,435	-0.68%

Table 1.0a Number of complaints to the GOC compared to the total number of registrants.

These numbers should be considered against the number of sight tests that are conducted annually. According to figures from the Optical Confederation publication, Optics at a Glance

2014, there were approximately 22.5 million sight tests conducted in 2013-2014. This equates to 0.00084% of sight tests resulting in a complaint to the GOC. It is clear that the rate of increase in complaints over the last two available years has increased at a much faster rate than the number of registrants.

1.2: What do professional guidelines say about the content of symptoms and history?

Even if a complaint against an optometrist is considered to have no merit by the General Optical Council's case examiners, poor record keeping can still become the subject of a lengthy and stressful hearing (Warburton, 2008). When such a hearing arises, the Association of Optometrists' Legal Services Team takes on the task of defense. An important element of defence is judging the optometrist's records against what is typical practice.

The College of Optometrists provide the "Guidance for Professional Practice" within the section (A20) that deals with record keeping (College of Optometrists 2015). The guidance suggests the following should be recorded:

1. Reason for visit
2. History and symptoms:
    - Symptoms, description and duration
    - If relevant, history of ocular and general health
    - Current general health
    - Medication
    - Family history of ocular and general health
    - Visual needs in terms of occupation, recreation or general activities
    - Whether the patient drives, with or without prescription, and
    - Previous optical prescription and date of last eye examination; approximate, if exact date is not known

The GOC code of conduct for individual registrants has the following items that relate to history and symptoms and patient records:

1. Maintain adequate patients' records;
2. Keep professional knowledge and skills up to date;
3. Be honest and trustworthy;
4. Respect and protect confidential information;
5. Make sure that personal beliefs do not prejudice patient care;
6. Act quickly to protect patients from risk where there is good reason to believe that you, or a colleague, may not be fit to practise, fit to undertake training, or in the case of a business registrant fit to carry on business as an optometrist, dispensing optician or both;
7. Never abuse your professional position;
8. Work with colleagues in the ways that best serve patients' interests;
   Be covered by adequate and appropriate insurance for practice in the United Kingdom throughout the period of your registration;
9. Ensure your conduct, whether or not connected to your professional practice, does not damage public confidence in you or your profession.

Clearly there is no detail included in either the guidance provided by the College of Optometrists or the GOC Code of conduct with regard to an exact definition of what should be recorded. Practitioners are therefore expected to practice to the standard of a reasonable competent optometrist. This test is taken to mean that when compared to their peers, would the practitioner’s actions or record keeping in this instance be acceptable to the majority of fellow practitioners?

The basis of this test rests within two famous law cases, the first is the case of Bolam Vs Friern Hospital Management (Jones, 2000; Pierscionek, 2008) and the second is Bolitho Vs City and Hackney Health Authority (Pierscionek, 2008).

The Bolam Vs Friern Hospital Management (1957) case centered around a salesman named John Bolam who was treated for depression by means of electroconvulsive therapy. He was not advised of the risks involved when consenting to the treatment. During his second course of treatment he sustained serious injuries including dislocated hip joints and a broken pelvis. He had been given no muscle relaxants and he was not restrained. Negligence was alleged against the hospital for allowing the procedure to take place without muscle relaxants and without proper restraints. Medical opinion was divided and the injuries sustained were said to be extremely rare. The judge presiding over the case, Justice McNair, informed the jury that *"A doctor is not guilty of negligence if he has acted in accordance with the practice accepted as proper by a responsible body of medical men skilled in a particular art".* Negligence was not proved.

The Bolitho Vs City and Hackney Health Authority (1998) case centered around a young boy of 2 years old who was admitted to hospital with breathing difficulties, allegedly secondary to croup. Croup is caused by a virus and often resolves spontaneously without intervention after a couple of days. The next day the child again had breathing difficulties and a nurse called for the doctor but the doctor did not attend. The child appeared to recover, but a few hours later the breathing difficulties returned. Once again the nurse called for the doctor, who once again did not attend. A short time later the child suffered a cardiac arrest and by the time normal cardiac function had been restored the child had become severely brain damaged. The parents of the child alleged negligence on the part of the health authority, on the basis that if the doctor had attended and intubated the child the cardiac arrest would not have occurred and the resulting brain damage could have been avoided.

Expert opinion was divided on whether intubation would have helped the child. The doctor who failed to attend was found to be negligent for failing to attend, but was found to not be responsible for the cardiac arrest and brain damage. The court preferred the opinion of an expert who stated that intubation would not have helped the child.

When looking at record keeping with regard to history and symptoms, the typical habits of optometrists are arguably more important than what they are taught to record. Researchers have attempted to define the selection criteria for a standard optometrist in order to establish a benchmark that other practitioners or staff could be judged against (Paudel et al., 2014). This research was to enable comparison to vision technicians in India. Even amongst a self-selecting cohort of optometrists, agreement was not perfect and there were still differences in accuracy of retinoscopy and disease diagnosis. Given that it could be, and has previously been, argued by Shah et al. (2010) that such a self-selecting group is likely to practice at a level higher than a normal optometrist, this makes the definition of a standard optometrist difficult.

1.3: What does Aston teach about the contents of symptoms and history?

Aston teaches second year optometry undergraduates how to record symptoms and history. These classes also introduce students to database and problem-orientated style eye examinations (Elliott, 2013).

Database style eye examinations are used in training clinics and were designed to enable detection of most visual system diseases by students with limited clinical experience. This style of examination is, however, considered to be less suitable for qualified optometrists who have the experience to adopt more efficient problem-orientated eye examinations (Elliott, 2013).

The literature suggests that the transition to problem-orientated eye examinations that takes place after graduation is difficult to teach in undergraduate classes (Elliott, 2013). Nevertheless, Aston's Virtual Patient was developed as part of an ongoing postgraduate research project to do just that.

The Virtual Patient has been used since 2011 to teach second year optometrists how to adopt efficient problem-orientated eye examinations. It reinforces the idea of "surviving" a lifetime in practice without litigation (Pane & Simcock, 2005). It provides students with approximately 250 Virtual Patient scenarios clustered into 22 presentation types (e.g. vision loss in white eye, non-traumatic red eye). It adopts the SOAP (Subjective, Objective, Analysis and Plan) approach to problem orientated eye examinations in which symptoms and history (the subjective element of SOAP) dictates the clinical tests to be carried out in the remainder of the eye examination (Macalister & Wickham, 2008; Elliott, 2013). It also adopts LOFTSEA (Location or Laterality, Onset, Frequency and occurrence, Type and severity, Self-treatment, Effect on patient, Associated or secondary symptoms) as an approach to following up reported symptoms (Elliott, 2013).

The content of symptoms and history depends on the presentation type and was informed by various text books (Jackson, 2014; Sallustio 2008a,b; Pane & Simcock, 2005; Loewenstein & Lee, 2004; Singh et al., 2001; Bezan et al., 1999).

The study described in this thesis considered those questions asked when symptoms were absent (routine eye examinations, see Table 1.1), and for ten symptomatic clinical presentations (see Tables 1.0b and 1.2 to 1.11).

Clinical Presentation Types
Routine
Vision Loss in a white eye
Non traumatic red eye
Diplopia
Irritation (eye/s watery, itchy, gritty, foreign body sensation)
Floaters
Photopsia
Visual field loss
Metamorphopsia
Pain
Headache

Table 1.0b symptomatic clinic presentation types.

Question	Relevance
Reason for visit (RFV)	main concern
Last eye examination (LEE)	last check-up
Last medical examination (LME)	last check-up
Occupation	visual demands
Visual display unit (VDU) user	visual demands
Driver	visual demands
Hobbies/sports	visual demands
Reduced/blurred vision	symptom check
Reduced/blurred vision type - distance	symptom check
Reduced/blurred vision type - near	symptom check
Asthenopia	symptom check
Headaches (unusual)	symptom check
Floaters (new)	symptom check
Photopsia	symptom check
Eye soreness or irritation	symptom check
Diplopia	symptom check
Patient ocular history – spectacles	current wear
Patient ocular history – contact lens wear	current wear / risk factor
Patient ocular history - eye injury/trauma	risk factor
Patient ocular history – eye treatment	risk factor
Patient medical history – smoking	risk factor
Patient medical history – medication	risk factor
Family ocular history – glaucoma	risk factor
Family medical history – diabetes	risk factor
Family medical history – systemic hypertension	risk factor
Any other symptoms	symptom check

Table 1.1. The 26 routine symptoms and history questions that Aston teaches second year optometry undergraduates to ask during database style eye examinations carried out in training clinics.

Question	Relevance
Reduced/blurred vision laterality	all conditions
Reduced/blurred vision onset	all conditions
Reduced/blurred vision duration of transient attacks	migraine, temporal arteritis, transient ischaemic attack, brain disease
Reduced/blurred vision type (central, peripheral, both)	all conditions
Asthenopia	ametropia, presbyopia
Headaches (unusual)	optic neuropathy, temporal arteritis, brain disease
Floaters (new)	retinal detachment, vitreous haemorrhage
Photopsia	retinal detachment, migraine, transient ischaemic attack, brain disease
Pain in or around eyes	optic neuropathy, migraine
Metamorphopsia	macular degeneration, diabetic maculopathy
Neurological symptoms	brain disease
Temporal arteritis symptoms	temporal arteritis
Patient ocular history - high myopia	retinal detachment
Patient ocular history - head trauma	retinal detachment
Patient ocular history – eye surgery	retinal detachment
Patient medical history – smoking	macular degeneration
Patient medical history – systemic hypertension	vitreous haemorrhage, retinal vascular occlusion, transient ischaemic attack
Patient medical history – diabetes	diabetic maculopathy, vitreous haemorrhage, retinal vascular occlusion
Patient medical history – heart problems	retinal vascular occlusion, vitreous haemorrhage, transient ischaemic attack
Patient medical history – medication – steroids	cataract, glaucoma
Family ocular history – macular degeneration	macular degeneration
Family ocular history– retinal detachment	retinal detachment
Family medical history – migraine	migraine
Differential diagnosis (19 conditions / 24 scenarios): **ametropia (treat), presbyopia (treat), migraine (advise, routine), cataract (advise, routine), dry macular degeneration (advise, routine), wet macular degeneration (urgent 1 week, same day), diabetic maculopathy (urgent 1 week), glaucoma - advanced chronic (soon), optic neuropathy (progressive - urgent 1 week, same day), optic neuropathy (acute - immediate), temporal arteritis (immediate), retinal detachment (same day), branch retinal vein occlusion (urgent 1 week), central retinal vein occlusion (urgent 1 week), branch retinal artery occlusion (immediate), central retinal artery occlusion (immediate), vitreous haemorrhage (same day), transient ischaemic attack (same day), brain disease (same day)**	
Tentative diagnoses possible from symptoms and history alone (10 conditions / 15 scenarios): **migraine (advise, routine), dry macular degeneration (advise, routine), wet macular degeneration (urgent 1 week, same day), optic neuropathy (progressive - urgent 1 week, same day), optic neuropathy (acute - immediate), temporal arteritis (immediate), retinal detachment (same day), vitreous haemorrhage (same day), transient ischaemic attack (same day), brain disease (same day)**	

Table 1.2. The 18 additional "vision loss in white eye" symptoms and history questions (plain text) that Aston teaches second year optometry undergraduates to ask during Virtual Patient problem-orientated style eye examinations. Four questions (bold italics) are mixed (problem-orientated and routine). Differential diagnosis includes 19 conditions (24 scenarios accounting for multiple plans). Hypothetically, 62% of the case scenarios could be diagnosed from symptoms and history alone.

Question	Relevance
Reported red eye laterality	all conditions
Reported red eye onset	conjunctivitis and episcleritis (for plan only)
Reported red eye frequency – recurrent	spontaneous subconjunctival haemorrhage, recurrent corneal erosion, marginal keratitis, non-infectious and infectious corneal ulcer, iritis
Reduced/blurred vision	dry eye, scleritis, recurrent corneal erosion, non-infectious and infectious corneal ulcer, iritis, endophthalmitis
Eye soreness or irritation	Bacterial and allergic conjunctivitis, dry eye, marginal keratitis
Pain in or around eyes	episcleritis, scleritis, recurrent corneal erosion, non-infectious and infectious corneal ulcer, iritis, acute glaucoma, endophthalmitis
Photophobia	dry eye, scleritis, recurrent corneal erosion, marginal keratitis, non-infectious and infectious corneal ulcer, iritis, endophthalmitis
Itchy eyes	allergic conjunctivitis, dry eye
Gritty eyes	bacterial conjunctivitis, dry eye
Foreign body sensation	dry eye, non-infectious and infectious corneal ulcer
Haloes around lights	acute glaucoma
Patient ocular history – contact lens wear	non-infectious and infectious corneal ulcer
Patient ocular history - eye injury/trauma	recurrent corneal erosion
Patient ocular history – red eye with blurred vision	marginal keratitis, non-infectious and infectious corneal ulcer, iritis
Patient ocular history – eye surgery	endophthalmitis
Patient medical history – smoking	marginal keratitis, infectious corneal ulcer
Patient medical history – allergies	allergic conjunctivitis
Patient medical history – recent cold	viral conjunctivitis
Patient medical history – systemic hypertension	spontaneous subconjunctival haemorrhage
Patient medical history – ankylosing spondylitis	iritis
Patient medical history – inflammatory bowel disease	iritis
Patient medical history – rheumatoid arthritis	dry eye, non-infectious corneal ulcer
<u>Differential diagnosis (14 conditions / 21 scenarios):</u> **allergic, bacterial and viral conjunctivitis (advise, urgent 1 week), spontaneous subconjunctival haemorrhage (advise, routine), dry eye (advise, routine, urgent 1 week), episcleritis (advise, routine), scleritis (urgent 1 week), recurrent corneal erosion (same day), marginal keratitis (same day), non-infectious and infectious corneal ulcer (immediate), iritis (same day), acute glaucoma (immediate), endophthalmitis (immediate)**	
<u>Tentative diagnoses possible from symptoms and history alone (13 conditions / 17 scenarios):</u> **allergic, bacterial and viral conjunctivitis (advise, urgent 1 week), spontaneous subconjunctival haemorrhage (routine), dry eye (advise, routine, urgent 1 week), episcleritis (advise), recurrent corneal erosion (same day), marginal keratitis (same day), infectious corneal ulcer (immediate), iritis (same day), acute glaucoma (immediate), endophthalmitis (immediate)**	

Table 1.3. The 16 expected additional "non-traumatic red eye" symptoms and history questions (plain text) that Aston teaches second year optometry undergraduates to ask during problem-orientated style eye examinations carried out using the Virtual Patient. Five questions (bold italics) are mixed (problem-orientated and routine). One question (grey) was only asked to decide upon a plan after conjunctivitis or episcleritis had been diagnosed and, because of this, was not included in this study. Differential diagnosis includes 14 conditions (21 scenarios accounting for plans). Hypothetically, 81% of the case scenarios could be diagnosed from symptoms and history alone.

Question	Relevance
Diplopia type - monocular, binocular	all conditions
Diplopia onset	all conditions
Diplopia occurrence	all conditions
Diplopia duration of transient attacks	migraine
Diplopia direction	uncompensated phoria, convergence insufficiency, thyroid eye disease, internuclear ophthalmoplegia, gaze palsy, nerve palsy, myasthenia gravis
Reduced/blurred vision	uncorrected astigmatism, dry eye, migraine, cataract, wet macular degeneration, keratoconus, thyroid eye disease, retinal detachment, intraocular lens dislocation
Increasing shadow or loss of vision that descended like a 'curtain'	retinal detachment
Asthenopia	uncorrected astigmatism, uncompensated phoria, convergence insufficiency
Headaches (unusual)	migraine, internuclear ophthalmoplegia, gaze palsy, nerve palsy
Headache changes in senses (aura)	migraine
Floaters (new)	retinal detachment
Photopsia	migraine, retinal detachment
Pain in or around eyes	thyroid eye disease
Neurological symptoms	internuclear ophthalmoplegia, gaze palsy, nerve palsy
Temporal arteritis symptoms	nerve palsy
Myasthenia gravis symptoms	myasthenia gravis
Patient ocular history - eye injury/trauma	retinal detachment
Patient ocular history - head trauma	retinal detachment
Patient ocular history – eye surgery	retinal detachment, intraocular lens dislocation
Patient medical history – smoking	wet macular degeneration, nerve palsy
Patient medical history – systemic hypertension	nerve palsy
Patient medical history – diabetes	nerve palsy
Patient medical history – thyroid problems	thyroid eye disease
Patient medical history – rheumatoid arthritis	dry eye
Patient medical history – multiple sclerosis	internuclear opthalmoplegia, nerve palsy
Family ocular history – retinal detachment	retinal detachment
Family medical history – migraine	migraine
Differential diagnosis (17 conditions / 26 scenarios): **uncorrected astigmatism (treat), uncompensated phoria (treat), convergence insufficiency (treat), dry eye (advise, routine, urgent 1 week), migraine (advise, routine), cataract (advise, routine), wet macular degeneration (urgent 1 week, same day), keratoconus (treat, routine), thyroid eye disease (urgent 1 week), retinal detachment (same day), intraocular lens dislocation (routine), internuclear ophthalmoplegia (same day), gaze palsy (same day), nerve palsy (same day, immediate), myasthenia gravis (urgent 2 weeks)**	
Tentative diagnoses possible from symptoms and history alone (14 conditions / 21 scenarios): **uncorrected astigmatism (treat), uncompensated phoria (treat), convergence insufficiency (treat), dry eye (advise, routine, urgent 1 week), migraine (advise, routine), wet macular degeneration (urgent 1 week, same day), thyroid eye disease (urgent 1 week), retinal detachment (same day), Internuclear ophthalmoplegia (same day), gaze palsy (same day), III nerve palsy (same day, immediate), IV nerve palsy (same day, immediate), VI nerve palsy (same day, immediate), myasthenia gravis (urgent 2 weeks)**	

Table 1.4. The 20 expected additional "diplopia" symptoms and history questions (plain text) that Aston teaches second year optometry undergraduates to ask during problem-orientated style eye examinations carried out using the Virtual Patient. Seven questions (bold italics) are mixed (problem-orientated and routine). Differential diagnosis includes 17 conditions (26 scenarios accounting for plans). Hypothetically, 82% of the case scenarios could be diagnosed from symptoms and history alone.

Question	Relevance
Irritation onset	allergic conjunctivitis (for plan only)
Watery eye	dry eye, blepharitis, ectropion, trichiasis, age-related nasolacrimal duct obstruction, punctal stenosis, foreign body on cornea or under eyelid, non-infectious or infectious corneal ulcer
Watery eye laterality	all conditions causing watery eye
Watery eye occurrence – seasonal	allergic conjunctivitis
Itchy eyes	allergic conjunctivitis, dry eye
Itchy eye laterality	all conditions causing itchy eye
Itchy eye occurrence – seasonal	allergic conjunctivitis
Gritty eyes	dry eye, blepharitis, allergic conjunctivitis (atypical)
Gritty eye laterality	all conditions causing gritty eye
Gritty eye occurrence – seasonal	allergic conjunctivitis (atypical)
Foreign body sensation	dry eye, trichiasis , foreign body on cornea or under eyelid, non-infectious or infectious corneal ulcer, allergic conjunctivitis (atypical)
Foreign body sensation laterality	all conditions causing foreign body sensation
Foreign body sensation occurrence – seasonal	allergic conjunctivitis (atypical)
Pain in or around eyes	non-infectious or infectious corneal ulcer
Reduced/blurred vision	dry eye, non-infectious or infectious corneal ulcer
Eye soreness or irritation	allergic conjunctivitis, dry eye, blepharitis, ectropion, trichiasis, foreign body on cornea or under eyelid
Photophobia	foreign body on cornea or under eyelid, non-infectious or infectious corneal ulcer, dry eye (atypical)
Patient ocular history – contact lens wear	non-infectious or infectious corneal ulcer
Patient ocular history - eye injury/trauma	foreign body on cornea or under eyelid
Patient ocular history – eye surgery	foreign body on cornea or under eyelid
Patient medical history – allergies	allergic conjunctivitis
Patient medical history – rheumatoid arthritis	dry eye, non-infectious corneal ulcer
Patient medical history – medication – eye drops	allergic conjunctivitis
Family medical history – hay fever	allergic conjunctivitis
Differential diagnosis (10 conditions / 17 scenarios): **allergic conjunctivitis (advise, urgent 1 week), dry eye (advise, routine, urgent 1 week), blepharitis (advise, routine), ectropion (routine, urgent 2 weeks), trichiasis (soon, urgent 2 weeks), age-related nasolacrimal duct obstruction (routine), punctal stenosis (routine), foreign body on cornea or under eyelid (treat, same day), non-infectious corneal ulcer (immediate), infectious corneal ulcer (immediate)**	
Tentative diagnoses possible from symptoms and history alone (7 conditions / 13 scenarios): **dry eye (advise, routine, urgent 1 week), blepharitis (advise, routine), ectropion (routine, urgent 2 weeks), trichiasis (soon, urgent 2 weeks), Foreign body on cornea or under eyelid (treat), foreign body on cornea or under eyelid (treat, same day), non-infectious corneal ulcer (immediate)**	

Table 1.5. The 19 expected additional "irritation (eye/s watery, itchy, gritty, foreign body sensation)" symptoms and history questions (plain text) that Aston teaches second year optometry undergraduates to ask during problem-orientated style eye examinations carried out using the Virtual Patient. Four questions (bold italics) are mixed (problem-orientated and routine). One question (grey) was only asked to decide upon a plan after allergic conjunctivitis had been diagnosed and, because of this, was not included in this study. Differential diagnosis includes 10 conditions (17 scenarios accounting for plans). Hypothetically, 76% of the case scenarios could be diagnosed from symptoms and history alone.

Question	Relevance
Floaters laterality	all conditions
Floaters onset	all conditions
Photopsia	retinal tear, retinal detachment
Patient ocular history - high myopia	retinal tear, retinal detachment
Patient ocular history – eye surgery	retinal tear, retinal detachment
Patient medical history – systemic hypertension	vitreous haemorrhage
Patient medical history – diabetes	vitreous haemorrhage
Patient medical history – heart problems	vitreous haemorrhage
Family ocular history – retinal detachment	retinal detachment
Differential diagnosis (5 conditions / 6 scenarios): **vitreous syneresis (advice), posterior vitreous detachment (advice), vitreous haemorrhage (same day), retinal tear (same day), retinal detachment (immediate, same day)**	
Tentative diagnoses possible from symptoms and history alone (3 conditions / 4 scenarios): **vitreous syneresis (advice), vitreous haemorrhage (same day), retinal detachment (immediate, same day)**	

Table 1.6. The 8 expected additional "floaters" symptoms and history questions (plain text) that Aston teaches second year optometry undergraduates to ask during problem-orientated style eye examinations carried out using the Virtual Patient. One question (bold italics) is mixed (problem-orientated and routine). Differential diagnosis includes 5 conditions (6 scenarios accounting for plans). Hypothetically, 67% of the case scenarios could be diagnosed from symptoms and history alone.

Question	Relevance
Photopsia laterality	all conditions
Photopsia onset	all conditions
Photopsia duration of transient attacks	migraine, transient ischaemic attack, brain disease
Photopsia occurrence – recurrent	migraine, brain disease
Photopsia type	all conditions
Floaters (new)	retinal tear, retinal detachment, vitreous haemorrhage
Neurological symptoms	brain disease
Patient ocular history - high myopia	retinal tear, retinal detachment
Patient ocular history – eye surgery	retinal tear, retinal detachment
Patient medical history – migraine	migraine
Patient medical history – systemic hypertension	transient ischaemic attack
Patient medical history – heart problems	transient ischaemic attack
Family ocular history – retinal detachment	retinal detachment
Family medical history – migraine	migraine
Differential diagnosis (6 conditions / 8 scenarios): **posterior vitreous detachment (same day), retinal tear (same day), retinal detachment (immediate, same day), migraine (advise, routine), transient ischaemic attack (same day), brain disease (same day)**	
Tentative diagnoses possible from symptoms and history alone (4 conditions / 6 scenarios): **retinal detachment (immediate, same day), migraine (advise, routine), transient ischaemic attack (same day), brain disease (same day)**	

Table 1.7. The 13 expected additional "photopsia" symptoms and history questions (plain text) that Aston teaches second year optometry undergraduates to ask during problem-orientated style eye examinations carried out using the Virtual Patient. One question (bold italics) is mixed (problem-orientated and routine). Differential diagnosis includes 6 conditions (8 scenarios accounting for plans). Hypothetically, 75% of the case scenarios could be diagnosed from symptoms and history alone.

Question	Relevance
Reduced/blurred vision laterality	all conditions
Reduced/blurred vision onset	all conditions
Reduced/blurred vision duration of transient attacks	migraine, transient ischaemic attack, brain disease
Reduced/blurred vision type (central, peripheral, both)	all conditions
Increasing shadow or loss of vision that descended like a 'curtain'	all conditions
Headaches (unusual)	optic neuropathy, brain disease
Floaters (new)	retinal detachment
Photopsia	retinal detachment, migraine, transient ischaemic attack, brain disease
Neurological symptoms	brain disease
Patient ocular history - high myopia	retinal detachment
Patient ocular history – eye surgery	retinal detachment
Patient medical history – smoking	macular degeneration
Patient medical history – migraine	migraine
Patient medical history – systemic hypertension	retinal vascular occlusion, transient ischaemic attack
Patient medical history – diabetes	retinal vascular occlusion
Patient medical history – heart problems	retinal vascular occlusion, transient ischaemic attack
Family ocular history – glaucoma	glaucoma
Family ocular history – macular degeneration	macular degeneration
Family ocular history – retinal detachment	retinal detachment
Family medical history – migraine	migraine
Differential diagnosis (13 conditions / 19 scenarios): **retinal detachment (immediate, same day), branch retinal vein occlusion (urgent 1 week), central retinal vein occlusion (urgent 1 week), branch retinal artery occlusion (immediate), central retinal artery occlusion (immediate), dry macular degeneration (advise, routine), wet macular degeneration (urgent 1 week, same day), glaucoma - chronic (routine, soon), optic neuropathy (progressive - urgent 1 week, same day), optic neuropathy (acute - immediate), migraine (advise, routine), transient ischaemic attack (same day), brain disease (same day)**	
Tentative diagnoses possible from symptoms and history alone (9 conditions / 14 scenarios): **retinal detachment (immediate, same day), branch retinal artery occlusion (immediate), dry macular degeneration (advise, routine), wet macular degeneration (urgent 1 week, same day), glaucoma - chronic (routine, soon), optic neuropathy (progressive - urgent 1 week, same day), optic neuropathy (acute - immediate), migraine (advise, routine), brain disease (same day)**	

Table 1.8. The 15 expected additional "visual field loss" symptoms and history questions (plain text) that Aston teaches second year optometry undergraduates to ask during problem-orientated style eye examinations carried out using the Virtual Patient. Four questions (bold italics) are mixed (problem-orientated and routine). One question (bold no italics) is routine. Differential diagnosis includes 13 conditions (19 scenarios accounting for plans). Hypothetically, 74% of the case scenarios could be diagnosed from symptoms and history alone.

Question	Relevance
Metamorphopsia laterality	all conditions
Metamorphopsia onset	all conditions
Patient medical history – smoking	all conditions
Patient medical history – systemic hypertension	central serous retinopathy
Patient medical history – diabetes	diabetic maculopathy
Patient medical history – heart problems	central serous retinopathy
<u>Differential diagnosis (6 conditions / 9 scenarios):</u> **dry macular degeneration (advise, routine), wet macular degeneration (urgent 1 week, same day), central serous retinopathy (soon), macular hole (routine, soon), epiretinal membrane (routine), diabetic maculopathy (urgent 1 week)**	
<u>Tentative diagnoses possible from symptoms and history alone (4 conditions / 6 scenarios):</u> **dry macular degeneration (advise, routine), wet macular degeneration (urgent 1 week, same day), central serous retinopathy (soon), diabetic maculopathy (urgent 1 week)**	

Table 1.9. The 6 expected additional "metamorphopsia" symptoms and history questions (plain text) that Aston teaches second year optometry undergraduates to ask during problem-orientated style eye examinations carried out using the Virtual Patient. One question (bold italics) is mixed (problem-orientated and routine). Differential diagnosis includes 6 conditions (9 scenarios accounting for plans). Hypothetically, 67% of the case scenarios could be diagnosed from symptoms and history alone.

Question	Relevance
Pain laterality	all conditions
Pain onset	all conditions
Pain duration of transient attacks	brain disease
Pain occurrence - recurrent	trigeminal neuralgia, brain disease
Pain type – 'shooting' or 'electric'	trigeminal neuralgia
Pain type – with eye movement	optic neuropathy
Reduced/blurred vision	iritis, glaucoma - acute, optic neuropathy, orbital cellulitis, orbital tumour, brain disease
Headaches (unusual)	glaucoma – acute, optic neuropathy, brain disease
Photopsia	brain disease
Photophobia	iritis
Diplopia	orbital cellulitis, orbital tumour, brain disease
Diplopia type - monocular, binocular	orbital cellulitis, orbital tumour, brain disease
Haloes around lights	glaucoma – acute
Neurological symptoms	brain disease
Temporal arteritis symptoms	optic neuropathy - acute
<u>Differential diagnosis (9 conditions / 11 scenarios):</u> **iritis (same day), glaucoma - acute (immediate), optic neuropathy (progressive - urgent 1 week, same day), optic neuropathy (acute - immediate), orbital cellulitis (immediate), orbital tumour (urgent 1 week), sinusitis (advise, routine), trigeminal neuralgia (routine), brain disease (same day)**	
<u>Tentative diagnoses possible from symptoms and history alone (9 conditions / 11 scenarios):</u> **iritis (same day), glaucoma - acute (immediate), optic neuropathy (progressive - urgent 1 week, same day), optic neuropathy (acute - immediate), orbital cellulitis (immediate), orbital tumour (urgent 1 week), sinusitis (advise, routine), trigeminal neuralgia (routine), brain disease (same day)**	

Table 1.10. The 11 expected additional "pain" symptoms and history questions (plain text) that Aston teaches second year optometry undergraduates to ask during problem-orientated style eye examinations carried out using the Virtual Patient. Four questions (bold italics) are mixed (problem-orientated and routine). Differential diagnosis includes 9 conditions (11 scenarios accounting for plans). Hypothetically, 100% of the case scenarios could be diagnosed from symptoms and history alone.

Question	Relevance
Headache laterality	all conditions
Headache onset (> or < 6 months ago)	all conditions
Headache onset - (gradual, sudden, transient)	all conditions
Headache occurrence - duration of transient attacks	migraine, brain disease
Headache occurrence – recurrent	migraine, brain disease
Headaches (unusual)	optic neuropathy, brain disease
Headache pattern - (stable, unstable)	all conditions
Headache worse when lying down	brain disease
Headache has noticeable effect on normal daily life	migraine, chronic daily headache
Headache frequency per month - (> or < 15 days)	migraine, chronic daily headache
Headache medication use per week - (> or < 2 days)	chronic daily headache
Headache changes in senses (aura)	migraine
Reduced/blurred vision	migraine, optic neuropathy, brain disease
Photopsia	migraine, brain disease
Pain in or around eyes	optic neuropathy, brain disease
Neurological symptoms	brain disease
Temporal arteritis symptoms	temporal arteritis
Vomiting	brain disease
Patient ocular history - head trauma	brain disease
Patient medical history – migraine	migraine
Patient medical history – systemic hypertension	possible cause of headache
Family medical history – migraine	migraine
Differential diagnosis (6 conditions / 7 scenarios): **chronic daily headache (routine), episodic tension type headache (advise), migraine (advise, routine), optic neuropathy (progressive - urgent 1 week, same day), optic neuropathy (acute - immediate), brain disease (same day)**	
Tentative diagnoses possible from symptoms and history alone (6 conditions / 7 scenarios): **chronic daily headache (routine), episodic tension type headache (advise), migraine (advise, routine), optic neuropathy (progressive - urgent 1 week, same day), optic neuropathy (acute - immediate), brain disease (same day)**	

Table 1.11. The 19 expected additional "headache" symptoms and history questions (plain text) that Aston teaches second year optometry undergraduates to ask during problem-orientated style eye examinations carried out using the Virtual Patient. Three questions (bold italics) are mixed (problem-orientated and routine). Differential diagnosis includes 6 conditions (9 scenarios accounting for plans). Hypothetically, 100% of the case scenarios could be diagnosed from symptoms and history alone.

Table 1.1 gives the database style questions that Aston expects optometry students to ask during training clinics. Tables 1.2 to 1.11 show that between 6 and 20 additional problem-orientated questions were expected of students conducting problem-orientated eye examinations with the Virtual Patient. These tables also show mixed questions; those used in both database and problem-orientated style eye examinations. In two tables (Tables 1.3 and 1.5), a problem-orientated question is only asked to decide upon the referral urgency of an eye condition. These questions were not studied in this thesis because, as described in chapter 3, only the history and symptoms text, and not the tentative diagnoses, were made available to the author.

Tables 1.2 to 1.11 also show tentative diagnoses and plans covered by each symptom presentation type in the Virtual Patient. A total of 64 tentative diagnoses are shown. Some of these have more than one plan, depending on their presentation characteristics (referred to as “scenarios” in Tables 1.2 to 1.11). Seven plans were possible: (1) “advise” (or treat), (2) refer “routine” (no specified time), (3) refer “soon” (within 1 month), (4) refer “urgent 2 weeks”, (5) refer “urgent 1 week”, (6) refer “same day” and (7) refer “immediate”. The 6 categories of referral urgency were based upon those adopted in Moorfield’s Manual of Ophthalmology (Jackson, 2014). A total of 148 different Virtual Patient “scenarios” are represented across the 10 symptom presentation types shown in Table 1.2 to 1.11.

In “teaching mode” the Virtual Patient guides students through problem-orientated eye examinations and automatically adjusts differential diagnoses at each step (i.e. after each question is asked and each test is completed). By this means, it was possible to determine at which point in the eye examination only a single tentative diagnosis remained. This occurred during symptoms and history in 114 (77%) of the Virtual Patient “scenarios”, and served as a reminder of the importance of this part of the eye examination (Ball, 1982). Tables 1.2 to 1.11 show that this hypothetical percentage varied from 62% to 100% depending on symptom presentation type. A figure of 83% had been suggested for medical outpatients (Hampton et al., 1975).

The relevance of the last point was that full adoption of the problem-oriented style questions shown in Tables 1.2 to 1.11 had the potential to arrive at tentative diagnoses early in the eye examination.

1.4.1: What does the research literature say about the methods of determining the contents of symptoms and history?

The study described in this thesis adopted record abstraction as a means of determining the contents of symptoms and history records. Record abstraction involves examining the entire record to analyse what is contained within the record, and to classify the information that is contained. Shah and her colleagues (Shah et al., 2010, 2009a, 2009b, 2009c, 2008, 2007) used standardised patient methodology to show that record abstraction did not accurately reflect the content of eye examinations; for symptoms and history, the proportion of false negatives (reported by the standardised patient but not recorded) ranged from 15% to 25%, and the proportion of false positives (not reported by the standardised patient but recorded) ranged from 3 to 4%. Nevertheless, the present study was about determining what is typically recorded, regardless of what the optometrist actually asked.

Research has been conducted within the field of medicine, where similar results were found to those of Shah (Dresslhaus et al., 2000). When looking at medical charts it was found that there was an underestimation of the quality of care delivered to patients. This poses the question that the records being examined in the present study also fail to accurately reflect the interactions with patients. This may be a fair point but in the case of a civil claim by a patient or investigation by the GOC, what is actually written in the patient record will still serve as a primary defense.

There is known to be disparity between what a practitioner records and what a patient can recall. When cancer-preventative services delivery was examined by making a comparison between self-reporting by patients and details recorded within medical records, agreement varied between 96% and 34% (Ferrante et al., 2008).

For example, it was noted that 13% of patients within the sample reported having not received a PSA screening test for prostate cancer, even though their medical records clearly recorded the result of the test. Although practitioners may under record the result of tests that they have conducted (Shah et al., 2007), it is clear that patient testimony cannot be relied upon as fact. This has implications for complaints that are referred to the GOC or that are handled in a civil claim. It is possible and also likely that the patient will have either mistaken or confused memories of an examination. Once again the record that the practitioner has conducted may be the only defense.

The under recording or failure to record the full details of consultations has been previously examined in research that compared the record keeping traits adopted when using computer records, paper records and hybrid systems. It was found that hybrid systems of record keeping led to a greater number of examinations being recorded. It was most likely that this was due to ease of access to paper based systems. It was also found that the quality of record keeping was highest in paper record systems. The researchers commented that the medico legal implications were clear and that the failure to record some or all of the notes led to practitioners losing a major piece of evidence, whilst also having a clear impact upon the continuity of care (Hamilton et al., 2003).

Alternative techniques for determining the content of eye examinations including the use of questionnaires, data abstraction, clinical vignettes and using standardised patients have all been used in previous studies. It was concluded that standardised patients were the “gold standard” because other forms of data collection led to various forms of bias (Shah et al., 2010). Unfortunately, the costs of training standardised patients to collect reliable data limited the amount of data collection that was possible.

The content of examinations and patient interactions have been looked at in various settings. When the reliability and validity of self-reporting was examined it was found that there was an overestimation of the number of tests that are actually carried out in everyday practice (Theodossiades et al., 2012). The conclusion was that self-reporting was fairly reliable for mandated tests, but not for tests at the discretion of the professional. The present study greatly reduces this problem, by examining what was actually recorded in a population that, at the time of recording, were unaware that their notes would be examined. This was also the case with the study by Theodossiades et al. This reduces the potential for practitioners to claim they have asked certain questions, in order to score more highly.

The use of vignettes for comparing clinical decision making has also been explored by Evans et al. (2015). Vignettes were also used by other researchers (Shah et al., 2010), where it was shown that they were a powerful tool that allowed some degree of control over the presentation types, and also allowed the possibility to present cases that may not be routinely encountered. It was however questioned whether vignettes could actually simulate real world situations given the limited scope that they impose.

1.4.2 Record abstraction

The use of record abstraction in the present study was a compromise. The sample being analysed was very likely to represent actual symptoms and history recording habits as it had not been influenced by external factors. The records being sampled were collected without the prior knowledge of the optometrists involved. This means that changes in clinical behaviour will not have taken place as a result of the study. Shah and her colleagues (Shah et al., 2009) suggested that this sort of external influence could lead to behavioral alteration and ultimately could bias data collected using questionnaires and clinical vignettes.

The process of behavior alteration is referred to as the Hawthorne effect and is also known as the observer effect (McCarney et al., 2007). The existence of the Hawthorne effect was questioned by Jones (1992) who reexamined the seminal papers which led to the Hawthorne effect being documented. Jones could find no evidence of the Hawthorne effect within the Hawthorne experiments, and concluded that the effect had become enshrined as received wisdom within the social sciences. Whether the effect exists or not is not a question for this piece of work. It does however seem safe to say that taking steps to negate the possibility of the Hawthorn effect cannot be to the detriment of the study.

The present study looks at what practitioners actually encountered and what they recorded, rather than how they react to a restricted non-real world presentation.

1.4.3: Challenges to record abstraction involving free text

The level of detail recorded following contact lens consultations was examined in a recent study. One of the results, that has particular relevance to the present study, is that 39% of participants used abbreviations but only 26% of these matched standard abbreviations recommended by one of the professional bodies (Wolffsohn et al., 2015a). This has particular significance for the planned use of automated text mining in the present study; unfamiliar and unique data entries are problematic as they are difficult to separate and detect within the text. This will be discussed in the section that follows on text mining.

Two polls to examine clinicians' views on the prospect of adopting a standardised structure for the recording of admissions to hospital were conducted. In these polls there was overwhelming support for this uniform approach to reduce errors and improve care (Carpenter et al., 2007). Whilst some clinicians have expressed reticence about the use of drop down boxes and predefined terms, it is clear that there are advantages to a more uniform and simplified recording system (Shah et al., 2010). The opinion of nurses with regard to electronic health records and standardised care plans was examined and it was found that nurse's had positive attitudes towards standardised care plans. The nurses were also of the opinion that not only could this lead to an increase in documentation, but also presented opportunities to develop the evidence base for care (Dahn & Wadenstein, 2008). The other undoubted advantage of standardised terms is that it aids the ease of extraction and audit of data. However, this standardisation needs to be applied at the point of data collection otherwise standardised forms alone cannot prevent omissions at the point of data gathering. Using computerised record keeping fields can be mandated so data has to be completely entered. When Pan et al. (2005) used a standardised form for data collection, missing data accounted for 19% of all discrepancies in the process.

1.5: What does the literature say about electronic text searches?

Due to the sheer volume of data that was available for this study, it was desirable to achieve record abstraction using electronic text searches. This section reviews the current methodologies.

1.5.1: Homographs, Homonyms and Polysemy

A homograph is a word that has the same form when written as another word, but has a different meaning and may be pronounced differently (OED Online 2016). Homographs present a problem for performing electronic searches when words have multiple meanings, as the search can struggle to tell if the word is the one that is required (Kulkarni et al., 2008). An example would be to search for the word "fire". Results will be returned with regard to "starting a fire" and to "open fire" as well as to "fire" someone. This problem was discussed by Subarani (2012), who opined that homographs could decrease the level of accuracy when using a text retrieval system. This was due to the confusion of making words that are different, appear to match. It was decided that this was the reason for a decrease in accuracy. Homonyms are words that have either the same spelling or pronunciation, but different meanings. (OED Online, 2016) If a word can be used to express different meanings, then it is said to be polysemous (OED Online, 2016). Polysemous words pose the same challenge as homographs. An example of a polysemous word is the word pupil, meaning both part of the eye and a student.

1.5.2: Synonyms

Synonyms are words that have the same meaning, but are spelt in different ways. An example would be words such as flammable and inflammable (OED Online, 2016).

The problem posed by homographs and synonyms is considered by Bauer (2014) and a structured glossary is suggested. This fits well with the view of the College of Optometrists with regard to only using approved abbreviations (College of Optometrists A19, 2015), and would appear the sensible approach if a system was being designed. Unfortunately, such a system is not in use.

1.5.3: Significance

Electronic text searches can also find it difficult to decide whether words have significance. (Cios et al., 2002). A search for the term glaucoma could return instances of “no glaucoma” and “family history of glaucoma”. Determining the relevance to the intended query can be time consuming or require advanced algorithms.

1.5.4: Inferences

Inferences are where a concept is discussed but the search term is not used (Graesser et al., 1994). An example would be a patient who it is noted is under the hospital for raised intraocular pressure and visual field loss and takes eye drops, yet the term glaucoma is not directly recorded.

1.5.5: Graphics

Electronic text searches can often not access information contained within diagrams and drawings. Within a clinical record this can fail to identify significant information. (Balasubramanian et al., 2006)

The challenges posed by non-standardised language and characters is evident within social media, where the numerous variations in language pose challenges for even developed text mining solutions. Maynard and colleagues attempted to use a variety of natural language processing tools to determine if it was possible to detect the subjectivity of the social media post and also the sentiment associated with the post. It was found that the differences in language within different social media settings altered the accuracy of different natural language processing tools to varying extents (Maynard et al., 2012).

Roy et al. (2007) stated that the use of electronic searches allows the easier and more rapid retrieval of articles, but can also tend to create more false positives which must be then sorted by the researcher. They were keen to emphasize that manual text searches are tedious and that this tedium can introduce errors of its own. It is their view that researchers should be aware of the benefits and drawbacks of manual and automated search processes. These are listed in the table 1.12.

Benefits	Drawbacks
Easier	False positives
Less tedious	False negatives
Rapid retrieval	Less accurate*
Less time consuming	Less thorough*
More thorough*	Visual features cannot be analysed
More accurate*	

Table 1.12. The advantages and disadvantages of automated text searches compared to manual text searches.
****Some items are both benefits and drawbacks and are dependent on the process used and the clarity of terms used. The researchers argue that the tedium involved in manual processing can make an automated process more accurate, whilst simultaneously the automated process may be less accurate. A similar problem exists for thoroughness.***

1.5.6 Text mining

What is text or data mining? It is the process of analysing text to extract the information that is of particular use to the researcher Witten et al. (2011). Text mining is also described by Tan (1999) as referring to the process of extracting interesting and non-trivial patterns or knowledge from text documents. Hotho (2005) attempted to define text mining by relating it to different areas of research and stated that for each area a different definition could be used. The three definitions that were decided upon were as shown in Table 1.13.

Definition of Text mining	Rationale
Information extraction	The extraction of facts from text
Text Data Mining	The application of algorithms and methods from machine learning and statistics to find useful patterns.
Knowledge Discovery in Database	Text mining used as a series of steps, information extraction is used along side data mining and/or statistical procedures.

Table 1.13. Definitions of text mining.

Hearst (2003) explained that text mining differs from a simple web search that we are all familiar with. He added that the more familiar search is generally used to find something that already exists. Text mining differs in that it aims to discover unknown information. For the present study, that unknown information is the symptom & history recording patterns of optometrists. Text mining differs from machine learning, in that text mining can be a done with or without machines, machine learning is the process of teaching a machine to make autonomous decisions.

Possible ways to utilise machine learning have been considered by Turney (1999), Frank et al. (1999), and Medelyan & Witten (2008). The original “Page-Rank” algorithm, that was designed for Google, used text mining to find and classify web pages (Brin & Page, 1998). Big data is often described as large scale data that is far larger than that normally captured by applications. The sheer volume of data present means that the applications of text mining are immediately apparent.

Text mining aims to find a way to convert text into a format that is suitable for computers to analyse or to enable people without the time to consume the entire text to find the parts that are relevant (Witten at al., 2011). The sheer volume of different words can make classification of documents difficult, and although certain words that occur frequently can be eliminated easily, it is actually the words that occur only once that pose the challenge for classification (Witten et al., 2011)

The lack of continuity within written text poses another problem. Different practitioners often spell words differently or incorrectly, which makes the process of data mining ever more difficult. Ex Libyan leader Muammar Gaddafi’s name can be found to be represented 47 different ways in documents that had been received by the USA Library of Congress (Witten et al., 2011).

Document clustering has been used by research teams to aid information retrieval for over 20 years (Martin, 1995). Other researchers have described how a large number of machine learning techniques have been applied and tested with regard to text categorisation. The same researchers commented that automated text categorisation is now comparable to text searches carried out by trained professionals (Sebastiani, 2002).

Work has been conducted on decision tree analysis as a form of machine learning (Brieman et al., 1984). Decision tree analysis is found in all modern statistics packages, and are regarded as a standard tool for data mining according to both Mitchel (1997) and Quinlan (1986). This is because they are quick and can scale easily. However, they are limited by the final decision making process being reliant on a few terms (Hotho, 2005). More about decision tree analysis will be said in section 3.2.4.

Text mining has been applied in multiple settings, as listed in Table 1.14.

Area of Use	Reference
Patent analysis	Koster et al. (2001)
News agencies	Paaß (2005)
Bioinformatics	Kim et al. (2004)
Spam email filtering	Michelakis. (2004)
Stock market analysis	Abdullah. (2013)
Social network analysis	Yu et al. (2012)
Biomedical research	Rebholz-Schuhmann. (2012)
Studying Indian languages	Hanumanthappa & Narayana Swarmy (2014)
Android malware analysis	Suarez-Tangil et al. (2014)
Financial fraud cases	Zaki & Theodoulidis (2013)
Cancer research	Zhu et al. (2013)
Customer experience feedback	Ordenes et al. (2014)
Web content	Johnson & Gupta (2012)
Financial investment modelling	Gu et al. (2015)
Construction safety	Li (2015)
Plagiarism detection	Rubini & Leela (2013)
Security threats	Inkpen (2016)

Table 1.14 Table showing various applications for text mining and short form supportive reference.

Success has been achieved in all of these settings, but many required pre-processing of the text to be mined to improve the results, along with complex algorithms. Pre-processing involves sorting and catergorising the document from a raw text format into a form that can be more easily mined for relevant information. Techniques include pre-classifying the document, removing certain classes of words and calculating the exclusivity of words. By calculating how exclusive a word is, the ability to use it to discriminate can be found (Vijayrani et al., 2011).

A form of data extraction has been used to integrate the electronic medical records of patients with primary open angle glaucoma (POAG) (Restropo et al., 2015). The researchers built an algorithm to detect episodes of POAG from both structured and unstructured data. Structured data, is data that is highly organised and therefore easily searchable. Unstructured data, in comparison, is the opposite, with no defined organisation and data assembled with no hierarchical structure (Inmon, 2006). Whilst the algorithm's ability to accurately predict outcomes was limited, there were encouraging signs that there was the potential for reasonable diagnostic accuracy if there was further development (Restropo et al., 2015). Attempts have been made to identify incidents of uveitis studies within the Medline database. By using a narrow algorithm and text mining, it was possible to make accurate predictions in just over half (Williams et al., 2013).

Text mining utilises Naïve Bayes classifiers to classify documents based upon the occurrence of certain words within them (Hotho, 2005). Naïve Bayes is used within text mining to calculate the likely document classification, by pooling the probabilities for each term within a document.

1.5.7 Naïve Bayes

Bayes Theorem of conditional probabilities is attributed to the Reverend Thomas Bayes (Bayes & Price, 1764) who described how the probability of an event changed based upon new evidence. The idea itself is relatively simple, the pre-test probability or initial belief, is altered depending on the availability of new evidence provided by further tests. The weight of the new evidence can be expressed as likelihood ratios and used to give a new and updated belief or post-test probability.

Bayes' theorem can be used to allow a machine or engine to self-learn. This allows accuracy to increase as more data becomes available.

The term naïve is used as it is necessary to make the assumption that all variables are independent of each other. Despite the simplification of Naïve Bayes to assume that all variables are independent, the results obtained are very comparable with those that can be obtained by more complex methods of data extraction. Therefore, although the independence assumption is often broken when real world data is used, Naïve Bayes still works well (Bijalwan et al., 2014).

It has been shown that one of the challenges with Naïve Bayes is that when the independence assumption was broken, the accuracy that was possible did not improve much as the database size increased. It was noted that the achievable accuracy asymptotes early, or in other words the accuracy quickly approaches the best achievable and then ceases to improve further. The addition of decision tree analysis improved, and in fact out performed, Naïve Bayes alone for larger databases. This hybrid approach combined the benefits of both decision trees and Naïve Bayes and was targeted towards larger datasets (Kohavi, 1996).

The use of decision trees has been shown to aid the understanding of Bayes' Theorem by providing a visual representation of the process. It has also been shown that this can aid the understanding of Bayesian analysis for non-mathematicians and particularly within the medico-legal setting (Fenton & Martin, 2010).

It has been suggested that clinical decision making is fundamentally Bayesian, and clinicians apply Bayesian reasoning in framing and revising differential diagnoses (Gill et al., 2005). These researchers further stated that a Bayesian approach was essential for interpreting surprising test results in the context of history taking and examination, such as a patient who reports good vision, but then is found to have reduced visual acuity on testing.

An example of the use of Bayesian thinking that may be encountered within optometric practice is in the diagnosis of glaucoma. Whilst naïve Bayes itself may not be applied directly, the process applied is very much Bayesian. If a patient presents with only a positive family history of glaucoma, the risk of glaucoma could be estimated. If the same patient then demonstrated sequentially a loss of visual field, raised intraocular pressure and a large degree of optic nerve head cupping, each new test would increase the certainty that the patient did indeed have glaucoma.

1.5.7.1 Traditional expression of Bayes' theorem

Aspinall & Hill (1983a) used conventional probability notation to describe Bayes theorem. Using this form of notation, the pre-test probability of a diagnosis is stated as p(D+). If a test is carried out and the result is positive, the post-test probability of that diagnosis is stated as p(D+|T+) and is calculated as shown below:

Where:

p(D+) = probability of a diagnosis (pre test)
p(T+|D+) = probability of a test being positive for a given diagnosis
p(D+|T+) = probability of a diagnosis given a test being positive (post test)

$$p(D+|T+) = \frac{p(T+|D+) \times p(D+)}{p(T+)}$$

1.5.7.2 Decision matrices

Aspinall and Hill (1983) also described diagnostic matrices (2x2 tables) that are a means of organizing the clinical data prior to applying Bayes' theorem (Table 1.15).

	Condition/Disease		
Test	**Present**	**Absent**	**Total**
Positive	A	B	A+B
Negative	C	D	C+D
Total	**A+C**	**B+D**	**A+B+C+D**

Table 1.15. A diagnostic matrix for the application of naïve Bayes.

The cells in the diagnostic matrix (Table 1.15) are explained below:

A+B+C+D = Total sample size.

A+C = Number of cases with a specific diagnosis.

B+D = Number of cases without a specific diagnosis.

A+B = Number of cases with a positive test result.

C+D = Number of case with a negative test result.

A = True positives = Positive diagnosis and positive test result.

B = False positives = Negative diagnosis and positive test result. (Type I error)

C = False negatives = Positive diagnosis and negative test result (Type II error)

D = True negatives = Negative diagnosis and negative test result.

Use of the diagnostic matrix to calculate pre-test probability, pre-test odds, sensitivity, specificity, likelihood ratios, post-test odds and post-test probability is described in sections that follow.

Type I Error = Test result is positive, but the disease is not present.

Type II Error = Test result is negative, but the disease is present.

1.5.7.3 Pre-test probability and odds

The probability of diagnosis prior to testing is calculated from the diagnostic matrix (Table 1.15) as below:

Pre-test probability = (A+C) / (A+B+C+D)

The pre-test probability is converted into odds:

Pre-test odds = Pre-test probability / (1 - Pre-test probability)

1.5.7.4 Sensitivity and specificity

Sensitivity is also referred to as the true positive rate (Altman & Bland., 1994). It is the proportion of people with disease that are correctly classified by the test as having disease. Expressed in terms of conditional probability it is the proportion of people who have tested positive given they have the disease. It can be expressed in conventional notation:

Sensitivity = p(T+|D+)

It can also be calculated from the simpler diagnostic matrix (Table 1.15):

Sensitivity = A / (A+C)

Specificity is also referred to as the true negative rate (Altman & Bland, 1994). It is the proportion of people without disease that are correctly identified by the test as not having disease. In terms of conditional probability, it is the proportion of people who have tested negative given that they are free of disease. In conventional notation it is expressed as:

Specificity = p(T-|D-)

It can also be calculated from the diagnostic matrix (Table 1.15):

Specificity = D / (B+D)

Sensitivity and specificity describe the accuracy of the test itself but it would be incorrect to deduce that a positive test result from a test with, for example, 95% sensitivity and specificity indicates, with 95% probability, that a person has disease. This mistaken interpretation has been described as the base-rate fallacy (Bar-Hillel, 1980). Likelihood ratios are required to determine the probability that a person has disease can be calculated from sensitivity and specificity.

1.5.7.5 Likelihood ratios

The likelihood ratio is essentially an odds ratio and is used to alter the degree of belief that disease is present or absent. Positive and negative likelihood ratios correspond to positive and negative test results and can both be derived from sensitivity and specificity:

Positive likelihood ratio = sensitivity / (1 - specificity)

Negative likelihood ratio = (1 - sensitivity) / specificity

A test with a likelihood ratio of 1 has no diagnostic value as it cannot raise or lower the degree of belief that disease is present. On the other hand, a very high likelihood ratio strongly indicates that disease is present. Similarly, a likelihood ratio close to zero strongly indicates that a person is disease free. If multiple tests are carried out, the product of their respective likelihood ratios is used to alter the degree of belief that disease is present or absent.

1.5.7.6 Post-test odds and probability

The post-test odds of disease are can be calculated using likelihood ratios as below.

For one positive test result:

Post-test odds = Pre-test odds x positive likelihood ratio

For one negative test result

Post-test odds = Pre-test odds x negative likelihood ratio

For multiple positive and negative test results:

Post-test odds = Pre-test odds x product of all positive and negative likelihood ratios

Post-test probability is calculated as below:

Post-test probability = post-test odds / (post-test odds +1)

1.6: Summary and scope of thesis

The primary purpose of the study described in this thesis was to determine whether Aston University's undergraduate lectures on the symptoms and history element of eye examinations reflected the habits of optometrists working in multiple-practice. This had never been investigated before and had the potential to (1) inform the profession about what is typical practice and (2) allow teachers to translate the study findings to teaching practice with a view to better preparing optometry students for a lifetime of work in multiple-practice.

Chapter 2: Estimated prevalence of presentation types

2.1 Introduction

The feasibility of carrying out Bayesian searches on free text symptoms and history fields was investigated in this part of the study. Free text fields are parts of electronic practice records into which optometrists type their findings, rather than selecting from drop down lists or tick boxes.

2.2 Methods and findings

Data abstraction was applied to the electronic eye examination records taken from one of the largest multiple practice chains in the United Kingdom. Company policy required optometrists to enter a single free text symptoms and history field. It was assumed that this practice was followed as it was stated by the professional services director for the company, that regular audits were employed to ensure adherence.

Clearance was granted from the Life and Health Sciences Research Ethics Committee at Aston University (project 495) to treat this study as a clinical audit as long as all records were fully anonymised so that neither the practitioner nor the client could be identified. Clearance was also given to analyse the data without the consent of the practitioner or the client. This removed the possibility of altered behavior due to the Hawthorn effect (see section 1.4.2). The ethical dilemma in this study was that while it would have been morally correct to ask practitioner / client consent to analyse their clinical records, refusal of consent might have added unwanted bias to the study findings. Fortunately, there was precedent for analysing records without consent if the study was treated as a clinical audit and if all data were anonymised and the study had been specifically exempt from the requirement for individual consent by a Research Ethics Committee (section 3.3 of the Guidelines for Researchers and for Research Ethics Committees on Psychiatric Research Involving Human Participants: http://www.rcpsych.ac.uk/files/pdfversion/cr82i.pdf). All of these conditions applied to the present study.

2.2.1 Record extraction, refinement and separation into UK regions

The free text fields and practice identification codes were obtained for every eye examination record stored for the month of August 2014; 117,689 records from 375 practices. Restricting data collection to just the text field and practice identification code maximised anonymity.

Only acceptable free text fields were analysed. Removal of 14,145 records (12% of the original sample) was necessary because they had empty free text fields. These empty fields existed because any interaction with the practice management system generated a field. For example, this would occur if a client bought a pair of sunglasses from a store or a pre-registration supervisor was demonstrating the system to their trainee.

Free text fields varied a great deal in length and it was considered that the longer records were those completed by pre-registration optometrists whose habits were unlikely to be typical of fully qualified optometrists. Shorter records often contained meaningless characters and had presumably been created when system demonstrations had been made. Therefore, the decision was made to use the Microsoft Excel LEN function to count the number of characters in each free text field and to only include records with character lengths within the inter-quartile range (153 to 428 characters). The inter-quartile range represented the lengths of typical text fields and would not have been distorted by those that were unusually long or short; the inter-quartile range being a non-parametric measure of dispersion.

Only one practice was represented in Jersey and so this data was removed as well. The reason for this was that regional variations in habits were of interest. The other regions contained many practices. Basing Jersey's data on just one practice will have biased the findings to just a few optometrists making comparisons with other regions meaningless.

The decision was also made to exclude records that were not full eye examinations. Contact lens aftercare examinations, dispensing appointments and follow-up eye examinations were removed.

A sample of 51,944 records (44% of the original sample) remained after all exclusions and it was assumed that these exclusions had not created unwanted bias.

Practice identification codes were used to place each record into one of 13 regions. These were dictated by the Nomenclature of Units for Territorial Statistics (NUTS) which are a geocode standard for referencing the subdivisions of countries for statistical purposes and were developed and regulated by the European Union (http://en.wikipedia.org/wiki/Nomenclature_of_Territorial_Units__for__Statistics - accessed 14 November 2014). The NUTS regions can vary each year but those referred to in this study (valid from 1 January 2012 to 31 December 2014) covered the period of data collection. Jersey was not assigned a NUTS region by the European Union and this was another reason for its exclusion. Table 2.1 shows the number of records analysed from each region.

Region	Number of records	Number of Practices
North West	4235	32
North East	1806	13
Yorkshire and Humber	3286	26
West Midlands	4727	31
East Midlands	3952	32
South West	4834	38
South East	9563	78
London	8079	40
East	4464	29
Scotland	3754	21
Wales	1515	20
Northern Ireland	697	7
Republic of Ireland	1032	7

Table 2.1 Regional distribution (according to the Nomenclature of Units for Territorial Statistics) of the 51,944 records analysed in this study.

2.2.2 Identification of search terms

As this was a feasibility study, the decision was made to limit searches to terms relating to the 11 presenting symptom types described in Chapter 1 (section 1.3).

Electronic searches were carried out using Microsoft Excel. All 51,944 records were entered into an Excel database. Records from the 13 regions were then copied into separate regional worksheets.

A search term worksheet provided an area in which a search term was entered and the results of electronic counts for that search term in each of the regional worksheets could be seen ‘at a glance’.

Electronic searches made use of the Excel SEARCH function which identified the location of the search term (and was not case sensitive) in each record. The location appeared as a value of 1 to 428 i.e. the position of the search term in records that had a maximum of 428 characters (see section 2.2.1). If the search term did not exist in a record then a value of 0 appeared.

The Excel COUNTIF function was used to count the number of records with location values of greater than zero. Counts made in each of the 13 regional worksheets were then passed to the search term worksheet.

This database set up achieved two functions. The first was that it allowed the author to identify search terms that appeared frequently enough in each region to be of potential value in later Bayesian searches. The second was to allow searches on 51,944 records without computer crashes; searching 13 separate regional worksheets worked faster with fewer crashes than searching all 51,944 records in a single worksheet.

Preliminary inspection of individual records and the author's own professional knowledge was used to gather long lists of potentially useful search terms for each presenting symptom. Each search term was entered into the database to establish how often it occurred, if at all, in each region. This process led to a shortlist of 388 potentially useful search terms.

It is worth mentioning at this point that it became evident that typographical errors and the use of non-standard abbreviations were common. Many optometrists also pasted in a template of symptoms and history questions prior to adding their clients' individual responses.

2.2.3 Generation of likelihood ratios for identified search terms

Likelihood ratios are used in Bayesian analyses to raise or lower the odds of an outcome (section 1.5.7.5). In this study, the outcomes were the existence of one or more of the 11 symptomatic clinical presentations (section 1.3). In the clinical setting, likelihood ratios are assigned to diagnostic tests. In this study, they were assigned to search terms used to establish the existence of presenting symptoms.

Generation of likelihood ratios could be considered as being the process of teaching a Bayesian search engine. This process required a teaching dataset of manually classified free text fields. The size the dataset needed could not be determined prior to testing because research had indicated that the speed of learning (the number of teaching cases required) depended on the complexity of the task. Kohavi (1996) demonstrated that, depending on the complexity of the data, the number of cases needed to achieve maximum learning using naïve Bayes classifiers could vary anywhere between 500 to 15000. So the dataset was made as large as time reasonably allowed and 1075 records were manually analysed.

The teaching dataset was representative of the larger sample of 51,944 records. It included between 17 and 176 records from each of the 13 regions shown in Table 2.1. The regional variations in the number of records also very closely matched those seen in Table 2.1; with no more than a 3% departure from the regional variation expressed as a percentage. Of the 375 practices included in the larger sample, 242 (65%) were included in the teaching dataset.

Manual classification of the 1075 records involved placing them in an Excel database and close scrutiny of the contents of each free text field to determine whether one or more of the 11 symptom presentation types were present. The records were classified according to the symptomatic presentation. The Excel SEARCH function was then used, as described in section 2.2.2, to identify the location, if present at all, of all 388 short listed search terms in each of the 1075 records. Some of the search terms did not exist in any of the 1075 records or only existed in small numbers. So, the decision was made to reject search terms with less than 3 (an arbitrarily chosen number) occurrences in the entire learning dataset. This left 163 search terms, see Table 2.2, for generating likelihood ratios. Table 2.2 shows search terms in order of frequency and therefore indicates those most commonly used.

Symptom presentation [number of search terms]	Search terms [frequency of each search term]
Routine (no symptoms) [6]	"routine" [312], "nv ok" [147], "dv ok" [82], "dv ok nv ok" [34], "dv & nv ok" [9], "dv & nv fine" [3]
Vision loss in white eye [11]	"worse" [102], "blur" [82], "not as good" [60], "not as clear" [31], "reduced" [16], "loss" [16], "nv worse" [16], "nv not as good" [11], "dv worse" [7], "nv not as clear" [7], "dv not as good" [6]
Non-traumatic red eye [9]	"redness" [129], "red eye" [52], "no redness" [19], "redness/" [15], "/redness" [8], "n redness" [5], "/red eye" [5], "red eye," [4], "redness n" [3]
Diplopia [34]	"dip" [93], "dip/" [91], "dip," [88], "diplopia," [72], "double" [46], "no dip" [40], "dipl/" [36], "double vision" [35], "dip x" [28], "diplopia/" [27], "dip n" [27], "horizontal dip" [21], "x dip" [20], "vertical dip" [18], "occ dip" [17], "double vision," [17], "no double" [16], "sees double" [10], "/dip" [9], "diplopia n" [8], ",dip" [7], ", dip" [6], "h dip" [6], "vert dip" [6], "dip ," [6], "dipl /" [6], "horiz dip" [5], "diplopia ," [4], "dipx" [3], "dip /" [3], "diplopia 0" [3], "diplopia /" [3], "v dip" [3], "monocular dip" [3]
Irritation (eye/s watery, itchy, gritty, foreign body sensation [23]	"water" [64], "epiphora" [27], "watery eye" [13], "epiphora," [7], "lacrimation" [5], "no water" [4], "eyes water" [4], "itch" [138], "itchy eye" [89], "itchy eyes, [15]", "no itch" [6], "itchiness" [4], "eyes itch [3]", "/itch" [3] "grit" [39], "gritty eye" [22], "gritty eyes," [5], "grittiness" [3], "fb" [34], "fb sensation" [23], "fb sensation," [11], "foreign body" [10], "foreign body sensation" [5]
Floaters [7]	"float" [514], "no float" [90], "x float" [35], "n float" [10], "occ float [9]", "shower" [6], "cobwebs" [4]
Photopsia [35]	"flash" [516], "no flash" [176], "flashes/" [122], "/flash" [100], "f/" [84], "flashing" [74], "flashing lights" [61], "photopsia" [34], "x flash" [29], "flashes x" [29], "occ flash" [27], "flashes n" [27], "/ flash" [13], "flash/" [12], "no f/" [12], "spark" [11], "zigzag" [11], "flash n" [9], "flashes /" [9], "disturbance" [9], "flicker" [9], "no photopsia" [7], "visual disturbance" [7], " fl," [6], "shimmer" [6], "/photopsia" [5], "no fl," [5], "photopsia/" [4], "coloured light" [4], "flashing lights/" [4], "fl/" [4], "flash x" [3], "flashes 0" [3], "fls/" [3],"no fls/" [3]
Visual field loss [11]	"shadow" [52], "curtain" [17], "scotoma" [16], "/shadow" [15], "In peripher" [13], "veil" [9], "no shadow" [5], "or shadow" [5], "no curtain" [4], "field loss" [4], "/curtain" [3]
Metamorphopsia [5]	"distort" [42], "distortion" [32], "distorted" [11], "wavy" [8], "or distort" [5]
Pain in or around eye [10]	"pain" [309], "no pain" [74], "sharp pain" [36], "pain in eye" [14], "eye pain" [12], "shooting pain" [10], "dull pain", [7], "pain around eye" [5], "x pain" [3], "occ pain" [3]
Headache [12]	"h/a" [162], "no h/a" [98], "migraine" [68], " ha" [49], "frontal" [23], "no ha" [18], "temporal" [9], "tension" [9], "h/a x" [6], " h/as x" [3], "occ h/a" [3], "no migraine" [3]

Table 2.2 The 163 search terms that occurred at least 3 times in the manually classified dataset of 1075 records used to identify the 11 symptom presentation types. Search terms are shown in frequency order.

Symptom presentation	Search terms [positive likelihood ratio]
Routine (no symptoms)	"dv ok nv ok" [9.8], "nv ok" [3.0], "dv & nv ok" [2.7], "dv & nv fine" [2.7], "dv ok" [2.6], "routine" [2.5]
Vision loss in white eye	"nv not as clear" [17434.2], "dv not as good" [14943.0], "not as clear" [74.6], "nv worse" [37.3], "not as good" [27.4], "nv not as good" [24.9], "worse" [4.8], "blur" [9.5], "reduced" [7.5], "dv worse" [6.2], "loss" [1.5]
Non-traumatic red eye	"red eye" [123.0], "redness" [5.8], "red eye," [7.5], "/red eye" [1.9], "redness/" [0.5], "no redness" [0.0], "/redness" [0.0], "n redness" [0.0], "redness n" [0.0]
Diplopia	"horizontal dip" [198180.8], "vert dip" [56629.8], "vertical dip" [169870.6], "sees double" [94367.7], "h dip" [56629.8], "horiz dip" [47193.1], "v dip" [28319.6], "monocular dip" [18882.9], "occ dip" [150.8], "diplopia ," [9.4], "double" [7.9], "double vision" [4.9], "dip" [2.6], "dip ," [1.9], "dip" [1.6], "double vision," [1.3], "diplopia n" [1.3], "/dip" [1.2], "dip n" [0.4], "diplopia," [0.3], "dipl/" [0.3], "dip," [0.2], "dip/" [0.0], "no dip" [0.0], "dip x" [0.0], "diplopia/" [0.0], "x dip" [0.0], "no double" [0.0], ", ", dip" [0.0], "dipl /" [0.0], "dipx" [0.0], "dip /" [0.0], "diplopia 0" [0.0], "diplopia /" [0.0],
Irritation (eye/s watery, itchy, gritty, foreign body sensation	"lacrimation" [18072.2], "eyes water" [14458.4], "epiphora" [93.9], "epiphora," [21.7], "water" [19.5], "watery eye" [43.32], "no water" [3.6], "gritty eye" [79505.3], "gritty eyes," [18072.2], "grit" [43.3], "grittiness" [7.2], "itchy eye" [231623.9], "eyes itch [10844.8]", "itchy eyes, [54209.3]", "itchiness" [14458.4], "itch" [20.1], "no itch" [7.2], "/itch" [1.8], "foreign body sensation" [18072.2], "fb sensation" [37.9], "foreign body" [32.5], "fb sensation," [16.2], "fb" [21.0]
Floaters	"occ float [50727.3]", "cobwebs" [16.9], "n float" [5.6], "shower" [2.8], "x float" [2.6], "float" [2.2], "no float" [0.2]
Photopsia	"zigzag" [71698.0], "shimmer" [39111.0], "coloured light" [26076.1], "occ flash" [169.3], "spark" [65.1], "flicker" [22.8], "flashing lights" [19.9], "flashing" [16.4], "photopsia" [7.3], "flashes 0" [3.3], "fls/" [3.3], "no fls/" [3.3], "fl/" [2.2], "photopsia/" [2.2], "flash n" [1.9], "flashes /" [1.9], "disturbance" [1.9], "/photopsia" [1.6], "flash" [1.5], "no photopsia" [1.1], "visual disturbance" [1.1], "flash/" [0.6], "/ flash" [0.5], "f/" [0.4], "/flash" [0.3], "flashes n" [0.3], "flashes/" [0.2], "no flash" [0.1], "x flash" [0.0], "flash x" [0.0], "flashes x" [0.0], "flashing lights/" [0.0], "no f/" [0.0], " fl," [0.0], "no fl," [0.0]
Visual field loss	"scotoma" [229.1], "In peripher" [50.9], "veil" [30.6], "shadow" [13.1], "curtain" [8.3], "no shadow" [0.0], "/shadow" [0.0], "or shadow" [0.0], "no curtain" [0.0], "/curtain" [0.0], "field loss" [0.0]
Metamorphopsia	"distorted" [234.1], "wavy" [163.9], "distort" [85.9], "distortion" [70.3], "or distort" [5.9]
Pain in or around eye	"shooting pain" [81108.6], "dull pain", [56778.5], "pain around eye" [40558.3], "sharp pain" [228.6], "pain in eye" [105.3], "eye pain" [89.1], "occ pain" [16.2], "pain" [4.6], "no pain" [0.0], "x pain" [0.0]
Headache	"h/a" [162], "no h/a" [98], "h/a x" [6], " h/as x" [3], " ha" [49], "no ha" [18], "occ h/a" [3], "frontal" [23], "temporal" [9],"tension" [9], "migraine" [68], "no migraine" [3]

Table 2.3 Positive likelihood ratios for the 163 search terms used to identify the 11 symptom presentation types. Search terms are shown in order of the positive likelihood ratio.

Decision matrices (see section 1.5.7.2) were constructed for all 163 search terms in relation to all 11 symptom presentation types; (163 x 11 =) 1793 decision matrices in total. Positive and negative likelihood ratios were calculated (as shown in section 1.5.7.5) for each of the 1793 decision matrices. Table 2.3 shows positive likelihood ratios for search terms that specifically related to each of the 11 symptom presentations. That is, for reasons of brevity, only 163 out of the 1793 positive likelihood ratios appear in the table. Table 2.3 shows search terms in order of positive likelihood ratio and therefore indicates those which were most useful; being those with very high likelihood ratios that strongly indicated the presence of corresponding presenting symptoms or those with likelihood ratios close to zero that strongly indicated the absence of corresponding presenting symptoms.

None of the 1793 negative likelihood ratios are shown in a table because these did not show the huge variations shown in Table 2.3 for positive likelihood ratios; they only varied from 0.06 to 1.56 with a mean of 1.0 and standard deviation of 0.07. It was therefore considered that a table of these values would add very little to illustrating the relative usefulness of each search term, seen in Table 3.3, and would be surplus to needs.

2.2.4 Accuracy of Bayesian searches carried out using generated likelihood ratios

Before using the positive and negative likelihood ratios, generated as described in section 2.2.3, to carry out naïve Bayesian searches on the larger sample of 51,944 records, an investigation was carried out on the accuracy of this process, again using the manually classified dataset of 1075 records.

Recall from section 1.5.7.3 that Bayesian searches require pre-test odds. In this study, these odds would need to be derived from some estimate of the prevalence of the presenting symptoms. The problem was that this information did not exist for the larger sample of

51,944 records. So it was necessary to carry out the Bayesian searches with uniform pre-test odds of unity. In other words, the pre-test odds of all presenting symptoms were given a value of 1; meaning that all were assumed to have a 50% chance of existing in every record. It could be argued that, because Bayesian analyses need to account for known variations in pre-test odds, the searches carried out in this thesis were not Bayesian at all. Nevertheless, as a first approximation, uniform pre-test odds of unity were adopted.

The use of uniform priors of unity greatly simplified naïve Bayesian searches. This is because the post-test odds of any given presenting symptom being present in a record was simply calculated by taking the product of the appropriate likelihood ratios for all 163 corresponding search terms. This was carried out using the Microsoft Excel PRODUCT function. Choosing appropriate likelihood ratios was also straight forward. If a search term was present in the record its associated positive likelihood ratio for that presenting system was included in the calculation. If, on the other hand, the search term was absent then its associated negative likelihood ratio was included.

By this means, post-test odds were calculated for all 11 presenting symptoms for every record. These odds were converted to post-test probability values as described in section 1.5.7.6. A presenting symptom was considered to exist in a record if its post-test probability exceeded a specified threshold value. To find the best threshold values to use, 10 values of 0.1 to 0.9 in steps of 0.1 were applied. Presenting symptoms detected at each threshold value were compared to those actually present in the 1075 manually classified records.

For each threshold value, true and false positives and negatives were determined from which sensitivity, specificity (see section 1.5.7.4) and diagnostic accuracy (see section 1.5.7.6) were calculated. In addition, the prevalence was estimated at each threshold by expressing the sum of the true and false positives as a proportion of the total sample of 1075. The optimum threshold for each symptom presentation type was that which gave rise to the closest match between the estimated and actual prevalence. Table 2.4 shows the actual prevalence, sensitivity, specificity, diagnostic accuracy, optimum threshold and estimated prevalence for each symptom presentation type.

Symptom presentation	Actual prevalence	Sensitivity	Specificity	Diagnostic accuracy	Optimum threshold	Estimated prevalence
Routine (no symptoms)	0.16	0.72	0.93	0.90	0.8	0.17
Vision loss in white eye	0.29	0.70	0.88	0.83	0.6	0.28
Non-traumatic red eye	0.12	0.84	0.97	0.95	0.9	0.13
Diplopia	0.10	0.91	0.99	0.99	0.8	0.10
Irritation (eye/s watery, itchy, gritty, foreign body sensation)	0.22	0.93	0.98	0.97	0.7	0.22
Floaters	0.15	0.68	0.94	0.90	0.9	0.14
Photopsia	0.13	0.88	0.98	0.97	0.9	0.14
Visual field loss	0.06	0.91	0.98	0.98	0.9	0.07
Metamorphopsia	0.04	0.91	0.99	0.98	0.9	0.05
Pain in or around eye	0.11	0.79	0.98	0.96	0.9	0.11
Headache	0.13	0.48	0.91	0.84	0.7	0.15

Table 2.4 Sensitivity, specificity and diagnostic accuracy of naïve Bayesian searches carried out with optimum thresholds (i.e. post-test probability cut off points) set to match estimated and actual prevalence as closely as possible for each of the 11 presentation types. These searches made use of positive and negative likelihood ratios for 163 search terms and were carried out on 1075 manually classified records. Uniform priors of unity were used for all searches.

Table 2.4 shows that different optimum thresholds (0.6 to 0.9) arose for each symptom presentation type. The thresholds shown are near optimum because estimated and actual prevalence were not always exactly matched. This was because threshold levels were varied in steps of 0.1. Near optimum was considered sufficient for the purpose of this study. The resulting diagnostic accuracy (83 to 99%) was remarkably high given the use of uniform priors of unity.

Further improvement of diagnostic accuracy would have required more lengthy manual identifications and so the decision was made to proceed with using the existing likelihood ratios to make searches for each presentation type in 51,944 records in order to determine their prevalence in multiple-practice.

Although the actual prevalence of each symptom presentation type (4 to 22%) was known for the manually classified dataset of 1075 records, they were not representative of the prevalence in the larger sample of 51,944 records. This is because each record in the dataset was deliberately selected from the larger sample because they contained one or more of the symptom presentation types of interest.

2.2.5 Estimated prevalence of symptom presentations

Naïve Bayesian searches were carried out on the larger sample of 51,944 records using the search terms identified in section 2.2.2, their associated likelihood ratios calculated as described in section 2.2.3, uniform priors of unity and the optimum threshold values derived as described in section 2.2.4. A Microsoft Excel worksheet was set up for the purpose of these searches and records from each region were, once again, searched within separate worksheets to prevent computer crashes. Table 2.5 shows the estimated prevalence of each symptom presentation class in each region that arose from these searches.

	Routine	Vis	Red	Dip	Irritation	Floaters	Phot	VFL	Met	Pain	HA
North West	25.6	21.1	5.7	3.6	4.9	12.6	5.5	5.5	0.2	1.5	7.2
North East	13.2	22.1	5.8	6.1	3.8	6.4	4.0	3.2	4.3	1.6	7.7
Yorkshire and Humber	26.1	20.6	5.0	1.9	10.0	5.5	1.0	2.5	0.2	5.4	6.7
West Midlands	28.8	18.9	5.5	2.1	5.3	6.4	1.4	2.2	0.5	4.1	8.0
East Midlands	22.6	21.9	6.5	2.3	7.5	9.2	2.3	3.0	0.4	4.4	5.8
South West	17.3	21.9	7.9	4.0	5.5	5.7	3.7	4.2	0.4	2.4	7.2
South East	25.2	19.8	6.7	3.3	5.1	4.1	1.6	2.7	1.2	2.2	8.7
London	33.9	20.8	6.3	3.2	9.0	4.5	2.0	3.0	0.2	4.2	7.9
East	33.5	21.9	8.1	3.6	4.2	6.0	1.7	2.6	0.3	1.6	9.3
Scotland	23.3	15.5	9.7	5.2	8.0	6.4	3.4	3.6	0.5	4.0	7.9
Wales	9.0	17.8	6.9	2.6	5.2	3.4	4.2	3.4	0.6	2.1	6.5
Northern Ireland	11.2	23.2	8.2	4.3	7.3	0.7	0.9	3.0	0.1	3.0	11.9
Republic of Ireland	17.1	17.7	7.7	2.1	10.1	1.5	0.8	4.0	0.1	1.9	5.7
ALL	25.4	20.3	6.8	3.3	6.4	6.0	2.4	3.2	0.6	3.1	7.8

Table 2.5. The estimated prevalence (%) of each of the 11 symptom presentation classes across 13 regions of the United Kingdom. These estimates arose from naïve Bayesian searches on 51,944 records. Searches made use of the 163 search terms shown in Tables 2.2 and 2.3, their associated likelihood ratios, uniform priors of unity and the 2.4. Presentation classes included no symptoms (routine), vision loss in white eye (Vis), non-traumatic red eye (Red), diplopia (Dip), irritation (eye/s watery, itchy, gritty, foreign body sensation), floaters, photopsia (Phot), visual field loss (VFL), metamorphopsia (Met), pain in and around the eye (Pain) and headache (HA).

The estimated percentage prevalence of each symptom presentation type is shown. As expected, there are some big differences in prevalence but there are also differences across regions. Both could be tested with Chi-square but, on a note of caution, this huge sample has massive statistical power and will, therefore, show up practically any differences as being statistically significant, one way to prevent this problem is to make the point at which statistical significance is achieved a function of the sample size. This enormous statistical power could have been handled by elevating the alpha level required to achieve statistical significance. This was not carried out as regional differences are considered later in this thesis (section 3.3.4)

Interesting discussion points are:

1. The high prevalence (9 to 34%) of routine (no symptoms) presentation types was, perhaps, to be expected given that many visitors to this type of multiple practice will have been motivated by the desire to buy new spectacles rather than the need for an eye examination. The founder of this multiple-practice had a video on YouTube https://www.youtube.com/watch?v=zKqcY3d-fbg in which he explained that his business philosophy was very much along those lines.
2. Diplopia had a higher prevalence (2 to 6%) than was expected. However, this included monocular and binocular diplopia. It is also well known that patients often confuse 'double vision' with blur.
3. The prevalence of non-traumatic red eye (5 to 10%) may reflect the number of clients that were also booked in for contact lens aftercare examinations. It may also reflect the fact that data collection took place in August during which allergic conjunctivitis may be fairly common.
4. The prevalence (4 to 10%) of ocular surface irritation (watery, itchy and gritty eye or foreign body sensation) was lower than expected given the known prevalence of dry eye (about 15%) (Paulsen et al., 2014) .
5. The prevalence (6 to 12%) of headaches was also lower than expected but this might reflect the relatively poor sensitivity (48%, see Table 2.4) of Bayesian searches for this symptom.
6. It was pleasing to see that the prevalence of the symptom presentation types covered by Aston's virtual patient simulator varied from 1 (for metamorphopsia) to 20 (for vision loss in white eye) cases per 100 seen. This provided justification for the inclusion of these presentation types in the teaching material and will also give optometry students some idea of how often they are encountered in the multiple-practice setting.

2.3 Summary

2.3.1 Key points

The purpose of this part of the study was to determine the feasibility of carrying out naïve Bayesian searches on free text symptoms and history fields. The decision was made to do this by searching for 11 classes of presenting symptoms. This would also indicate the percentage prevalence of key presenting symptoms that features in Aston's classes on the symptoms and history element of eye examinations (see section 1.3). These searches proved to be very labour intensive. This part of the study showed that similar Bayesian searches on the more complex and numerous elements of complete symptoms and history "free text" fields might have been successful but would not have been feasible within the time frame of this study.

2.3.2 Study limitations

Searches were carried out with uniform priors that did not account for the prevalence of each presentation type across the UK (as this was unknown). It was assumed that that the use of optimum thresholds chosen to match estimated and known prevalence in the dataset of 1075 manually classified records would overcome this problem. The prevalence shown in Table 2.5 should therefore be considered with caution.

Table 2.4 shows that the sensitivity of the naïve Bayesian searches varied from 43 to 93%. This could have been improved by finding more search terms and calculating likelihood ratios on more records but this would have taken more time than was available to the author.

A major lesson had been learned from this exercise; that Bayesian searches of "free text" fields was not efficient. More sophisticated forms of text mining may have helped but the author was aware of discussions that had taken place at Aston University with a company that carried out Bayesian searches through social media in order to determine the public's political views. This company cannot be named for reasons of commercial sensitivity but it claimed to be world leading in these types of searches. When asked if their Bayesian searches could be applied to "free text" fields in optometry practice records they considered that records of this sort were too complicated. This lead to the notion that use of "free text" fields in practice records are an obstacle to large scale epidemiological studies that could inform the profession. Records with drop down menus of standardised clinical terms would be far more useful.

The original hope was that Bayesian type searches of the type described in this chapter would facilitate study of the content of symptoms and history examinations across the UK. However, given the time taken to complete searches for just 11 symptom presentation types, not to mention the above mentioned sources of error, the decision was made to abandon this search methodology for the far greater number of symptom and history items looked at in the next chapter.

Chapter 3: Estimation of the content of symptoms and history items recorded by optometrists in multiple-practice

3.1 Introduction

The study described in this chapter was designed to answer three questions.

The first question related to whether Aston's classes reflect what is typically recorded in multiple-practice, the destination of most optometry graduates. The author also currently teaches optometric law at Cardiff University and was a clinical adviser to the Association of Optometrists' legal team. The legal team was frequently called upon to defend optometrists facing fitness to practice processes. The basis of the team's defense often rests on how well the defendant's eye examination record reflected what would have been expected of a typical optometrist. This was largely left to opinion, frequently not supported by evidence. Therefore, answering this first question also provided an opportunity to gather evidence of value to the legal team.

Given that Aston's classes used virtual patient software to safely introduce the idea of problem-orientated examinations for 11 presenting symptom types, the second question related to whether there were variations in the conformity between what is taught and what is recorded for each type of symptom presentation.

Aston's optometry students were encouraged to use database style questions when seeing real patients due to their lack of experience. Asking every patient the same database style questions safely covered the vast majority of eye problems but led to long testing times and risked leaving too little time to ask more probing questions relating to specific complaints. The third question covered the extent to which this transition actually happened in multiple-practice.

The original plan was to find answers to these questions by searching all 51,944 free text symptoms and history fields for 105 database and problem-orientated questions covered in Aston's classes (see section 1.3). However, the study described in chapter 2 indicated that this was not feasible. Instead detailed manual searches were carried out on a much smaller dataset. The methods and findings of this smaller study are described in this chapter.

3.2 Methods

3.2.1 Record selection

Records were selected from the database of 1075 "free text" fields that had already been manually classified as containing one of more of the 11 presenting symptom types (see section 2.2.2). The original aim was to select three records for each symptom presentation type across each UK region; a total of 429 records. This would provide 33 records for each of the 13 regions and 39 records for each of the 11 symptom presentation classes. Records with multiple presentation types were to be excluded as this would complicate analyses.

Software used to calculate statistical power (GPower 3.1) indicated that at least 30 records were required to achieve 80% power for Cohen's standard medium effect size at an alpha level of 0.05 when using a variety of non-parametric statistical tests (i.e. the Kruskal- Wallis test for comparing three or more independent samples, the Mann-Whitney U test for comparing two independent samples and the Wilcoxon test for comparing two related samples). At least 30 records were also required to calculate binomial confidence limits for the estimated proportions of optometrists asking various questions.

Unfortunately, 429 suitable records could not be found in the 1075 classified records. A new decision was made to, instead, select at least 30 records for each symptom presentation type while aiming to gather as large a spread of records from across the UK regions as was possible; 330 records in total.

The thinking here was that variations in the symptoms and history questions asked for different symptom presentation types was the most important question. This would indicate how well Aston's teaching reflected real practice. Regional variations were of interest but were not the main study objectives. Initial thoughts were that each record should represent different practices (there were 374 practices, excluding 1 from Jersey, to select from) and to ensure that each record represented a single presentation type. The requirement for each record to represent different practices would increase the chance that the 330 selected records would have been written by 330 different optometrists working in different practices and single presentation types would allow uncomplicated comparisons of symptoms and history questions asked for each. However, selection of 330 acceptable records from different practices proved to be unachievable.

A further compromise was made. Records could be selected from the same practices and the co-existence of presentation types in individual records was allowable.

The final record selection criteria for this study were as follows:

1. Contact lens aftercare, follow up or recheck examinations were excluded;
2. Records had to contain at least 2 out of 3 entries relating to ocular, medical and family history (as this ensured that history was recorded in the “free text” fields analysed).
3. Selected records were ideally to be from different practices from as wide a spread of regions as possible but this rule was relaxed when necessary;
4. Records with single or coexisting presentation types were included. This led to instances where a selected record appeared under more than one presentation type.

Statistical advice (Dr Richard Armstrong pers. comm.) was sought on whether this would confound comparisons of proportions of questions asked for different presentation types and the advice was that it would not. The advice received was that it was not a concern.

Using the selection criteria adopted above a total of 224 records were identified and their distribution across each presentation type and UK region is shown in Table 3.1.

	Routine	Vis	Red	Dip	Irritation	Floaters	Phot	VFL	Met	Pain	HA	Totals
North West	3	5	2	3	3	4	3	4	3	2	3	35
North East	3	4	1	3	1	1	3	0	2	1	2	21
Yorkshire and Humber	3	9	0	3	3	2	0	4	2	2	3	31
West Midlands	3	4	4	3	3	2	4	2	5	4	3	37
East Midlands	3	6	3	1	3	3	6	5	1	4	3	38
South West	3	3	3	3	2	3	3	3	2	1	3	29
South East	3	3	6	3	4	5	6	2	6	5	4	47
London	3	5	4	3	3	4	4	5	4	5	3	43
East	2	6	4	3	3	3	3	3	3	5	4	39
Scotland	1	3	3	3	3	2	3	1	2	1	1	23
Wales	1	1	0	0	1	0	1	0	0	0	0	4
Northern Ireland	0	0	0	1	1	1	0	1	0	1	1	6
Republic of Ireland	2	1	0	1	0	0	0	0	0	1	1	6
Totals	30	50	30	30	30	30	36	30	30	32	31	359

Table 3.1 The representation of 11 symptom presentation classes and 13 regions of the United Kingdom in the 224 records selected for this study. The column and row totals show that there were at least 30 records representing each symptom presentation type but that this minimum sample size was not achieved for each region. A single record could appear in several cells if it contained multiple presentation types. This is the reason why the total count of 359 is higher than 224. Symptom presentation classes included no symptoms (routine), vision loss in white eye (Vis), non-traumatic red eye (Red), diplopia (Dip), irritation (eye/s watery, itchy, gritty, foreign body sensation), floaters, photopsia (Phot), visual field loss (VFL), metamorphopsia (Met), pain in and around the eye (Pain) and headache (HA).

Table 3.1 shows that records appeared under more than one presentation type (224 / 359) 38% of the time. The 224 selected records were taken from 163 practices; so might only represent 163 optometrists (assuming that no optometrist works in more than one practice).

Of course, more than one optometrist may work in the 163 practices included. A more detailed breakdown of the distribution of records in the 163 practices follows:

1. 121 practices were the source of only 1 selected record each;
2. 31 practices were the source of 2 selected records each;
3. 6 practices were the source of 3 selected records each;
4. 4 practices were the source of 4 selected records each;
5. 1 practice was the source of 7 selected records.

Table 3.1 also shows that there were at least 30 records for each symptom presentation type which meant that this study had the statistical power to identify variations in symptoms and history items recorded for each presentation type. On the other hand, 6 of the 13 UK regions has less than 30 records meaning that this study may not have the power to identify variations in recorded symptoms and history items across the UK, unless these variations were very large. This, however, was not one of the three key questions of this study.

Coexistence of symptom presentation types was the reason why some symptom presentations were covered by more than 30 records. A breakdown of records with coexisting presentation types is shown in Table 3.2.

Coexisting symptoms	Routine	Vis	Red	Dip	Irritation	Floaters	Phot	VFL	Met	Pain	HA	Totals
1	30	0	16	10	11	5	11	9	14	13	2	121
2	0	31	10	15	13	14	19	11	13	9	15	75
3	0	16	4	4	5	7	4	6	3	9	14	24
4	0	3	0	1	1	4	2	4	0	1	0	4

Table 3.2. The distribution of coexisting presentation types in the 224 records selected for this study. Symptom presentation classes included no symptoms (routine), vision loss in white eye (Vis), non-traumatic red eye (Red), diplopia (Dip), irritation (eye/s watery, itchy, gritty, foreign body sensation), floaters, photopsia (Phot), visual field loss (VFL), metamorphopsia (Met), pain in and around the eye (Pain) and headache (HA).

Table 3.2 shows that 54% (121 / 224) of the records had just 1 symptom presentation type. This was true for all of the routine presentation type records (as, by definition, these were asymptomatic). In contrast, this was true for none of the records with the 'vision loss in white eye' presentation type. The remaining records had between 2 and 4 coexisting presentation types. The complication caused by records with coexisting presentation types was that the habits of optometrists that made these records became disproportionately over-represented in the analysis. This was unavoidable and was a limitation of this study that should be borne in mind.

3.2.2 Identification of expected symptoms and history items

Details of the 105 symptoms and history questions that Aston expected its optometry students to ask are given in section 1.3.

Table 3.3 shows the numbers of database and problem-orientated questions expected in records containing just one symptom presentation class.

Question types	Routine	Vis	Red	Dip	Irritation	Floaters	Phot	VFL	Met	Pain	HA
Database	26	26	26	26	26	26	26	26	26	26	26
Problem-orientated	0	18	16	20	19	8	13	15	6	11	19
Total	26	44	42	46	45	34	39	41	32	37	45
“Issue”	0	3	0	6	0	0	1	1	0	3	6

Table 3.3. The number of database and additional problem-orientated symptoms and history questions expected for records with just one symptom presentation class according to what is taught at Aston University. The 26 database questions had to be asked regardless of the symptom presentation class. Specific symptoms required additional problem-orientated questions. The total number of questions included database and problem-orientated questions. “Issue” questions are also shown, these are questions that are reliant on another question being asked to necessitate the subsequent question. Symptom presentation classes included no symptoms (routine), vision loss in white eye (Vis), non-traumatic red eye (Red), diplopia (Dip), irritation (eye/s watery, itchy, gritty, foreign body sensation), floaters, photopsia (Phot), visual field loss (VFL), metamorphopsia (Met), pain in and around the eye (Pain) and headache (HA).

Table 3.3 shows that 26 database questions were expected to be asked regardless of the symptoms reported. These items were confirmed with tutor (Dr Amy Sheppard pers. comm.)

at Aston who was in charge of teaching undergraduate students what was expected in routine eye examinations.

Table 3.3 also shows that the 10 specific symptom presentation classes called for between 6 and 20 additional problem-orientated questions.

All 105 questions were entered into a Microsoft Excel database. The Excel IF function was used to identify which of the 105 symptoms and history items was expected to be asked for each of the 224 selected records. In the absence of coexisting presentation types then between 26 and 45 symptoms and history questions were expected. As almost half of the selected records had coexisting presentation types then between 26 and 68 (median = 43) symptoms and history questions were expected for each record, according to what is taught at Aston.

3.2.3 Manual detection of recorded symptom and history items

The author read all 224 records in order to manually detect which of the expected questions actually appeared.

Some of the problem-orientated questions only needed to be asked under certain circumstances. For example, some questions were only required if the client was over a certain age. The exact age of the client rarely appeared in the free text fields examined (as they will have been entered in other parts of the electronic practice record). So judgements had to be made as to whether these were expected to be asked and these judgements were sometimes difficult to make. These judgements were therefore, another limitation of this study that need to be borne in mind. These questions were referred to as “issue” questions and Table 3.2 shows that 6 of the symptom presentation classes had between 1 and 6 of these.

By this means, the proportion of expected symptoms and history items actually asked was determined for all 105 items.

3.2.4 Statistical analysis

All statistical analyses were carried out using SPSS version 21. As mentioned in section 3.2.1, use of GPower 3.1 had indicated that at least 30 records were required to achieve 80% power for Cohen’s standard medium effect size at an alpha level of 0.05 when using a variety of non-parametric and parametric statistical tests (non-parametric/parametric tests: Kruskal- Wallis test / One way ANOVA for comparing medians/means of three or more independent samples, the Mann-Whitney U test / unpaired t-test for comparing medians/means of two independent samples and the Wilcoxon test / paired t-test for comparing medians/means of two related samples). The Kolmogorov-Smirnov test was used to test samples of data for normal distribution prior to testing with non-parametric or parametric statistical tests. If data were not normally distributed, an attempt was made to make transform the data prior to retesting for normality with the Kolmogorov-Smirnov test repeated.

Decision tree analyses were also carried out. These are multivariate tests that can be conducted on mixed continuous and discrete variables and account for otherwise confounding interrelationships between all entered variables. Unlike other multivariate analyses, they also indicate the hierarchical relationship between variables in the form of a decision tree that can be readily interpreted. Tree growth and the grouping of each variable are carried out automatically, thereby removing any subjectivity on the part of the investigator. The CHAID (Chi-squared Automatic Interaction Detection) tree growing method was adopted. Both decision tree analysis and CHAID were available in SPSS and have been used previously to carry out multivariate analyses in the field of optometry (Ruston et al., 2016; Dunstone et al., 2013; Guillon & Maissa, 2005). Tree growing depth was set to 10 so that the levels of allowable branching exceeded the number of variables entered (which was not more than 6 in this study). To branch, a parent node needs sufficient data to create two of more child nodes. The minimum size of parent and child nodes was set at 20 and 10 to minimise restrictions on branching. Statistical advice (Dr Richard Armstrong, pers. comm.) indicated that it was not possible to calculate statistical power for decision tree analyses other than to adopt the “15 DF” rule. This almost forgotten rule (Ridgman, 1975) and its rationale is that experimental designs with residual errors of greater than 15 degrees of freedom gain little extra power as a result of further increases in sample size. The Decision Tree Analyses carried out later far exceeded this value.

3.3 Findings

3.3.1 Do Aston’s classes reflect what is typically recorded in multiple-practice?

Table 3.4 to 3.8 provide answers to the first question asked in section 3.1. Expected questions were typically asked between 0 and 88% of the time. Eighty (79%) of the expected questions were typically asked less than 50% of the time and 18 (17%) of the questions were never asked.

The legal team of the Association of Optometrists would most likely base their evidence on what typical optometrists ask on those questions asked more than 50% of the time according to the lower 95% confidence interval. Only 15 (14%) of the questions met these criteria.
No attempt was made to determine how often an expected question was answered negatively. This was considered beyond the scope of the present study, which was designed to determine how often a question was asked, regardless of the answer.

Question	Percentage asked		
	%	95% confidence limits	
		lower	upper
Reason for visit (RFV)	88	84	93
Last eye examination (LEE)	65	58	71
Last medical examination (LME)	0	0	1
Occupation	29	23	35
Visual display unit (VDU) user	39	32	45
Driver	49	43	56
Hobbies/sports	18	13	23
Reduced/blurred vision	75	69	81
Reduced/blurred vision type - distance	44	37	50
Reduced/blurred vision type - near	46	39	53
Asthenopia	2	0	4
Headaches (unusual)	67	60	73
Floaters (new)	54	47	61
Photopsia	61	54	67
Eye soreness or irritation	17	12	22
Diplopia	60	54	67
Patient ocular history – spectacles	38	32	45
Patient ocular history – contact lens wear	13	8	17
Patient ocular history - eye injury/trauma	14	9	18
Patient ocular history – eye treatment	41	35	48
Patient medical history – smoking	4	1	7
Patient medical history – medication	92	88	96
Family ocular history (parent or sibling) – glaucoma	53	46	59
Family medical history (parent or sibling) – diabetes	46	39	53
Family medical history (parent or sibling) – systemic hypertension	5	2	8
Any other symptoms	0	0	0

Table 3.4. Percentage (with 95% confidence limits) of the 26 expected database symptoms and history questions asked. These estimates arose from manual searches of 224 "free text" fields. "issue" questions did not arise.

Question	Percentage asked		
	%	95% confidence limits	
		lower	upper
Reduced/blurred vision laterality	40	28	51
Reduced/blurred vision onset	51	40	63
Reduced/blurred vision duration of transient attacks	**32**	**11**	**52**
Reduced/blurred vision type (central, peripheral, both)	25	15	35
Increasing shadow or loss of vision that descended like a 'curtain'	20	10	31
Headache laterality	6	0	15
Headache onset - (gradual, sudden, transient)	0	0	0
Headache onset (> or < 6 months ago)	10	0	20
Headache occurrence - duration of transient attacks	**0**	**0**	**0**
Headache occurrence – recurrent	10	0	20
Headache pattern - (stable, unstable)	10	0	20
Headache worse when lying down	3	0	9
Headache has noticeable effect on normal daily life	**0**	**0**	**0**
Headache frequency per month - (> or < 15 days)	**18**	**0**	**41**
Headache medication use per week - (> or < 2 days)	**0**	**0**	**0**
Headache changes in senses (aura)	**64**	**35**	**92**
Floaters laterality	37	19	54
Floaters onset	73	58	89
Photopsia laterality	42	26	58
Photopsia onset	67	51	82
Photopsia duration of transient attacks	**25**	**11**	**39**
Photopsia occurrence – recurrent	58	42	74
Photopsia type	89	79	99

Table 3.5. Percentage (with 95% confidence limits) of the expected additional problem orientated symptoms questions asked with respect to vision loss, headache, floaters and photopsia. These estimates arose from manual searches of 224 "free text" fields. "Issue" questions are shown in bold.

Question	Percentage asked		
	%	95% confidence limits	
		lower	upper
Pain in or around eyes	27	19	34
Pain laterality	63	46	79
Pain onset	69	53	85
Pain duration of transient attacks	**20**	**2**	**38**
Pain occurrence - recurrent	38	21	54
Pain type – 'shooting' or 'electric'	6	0	15
Pain type – with eye movement	3	0	9
Photophobia	20	11	29
Diplopia type - monocular, binocular	**17**	**3**	**30**
Diplopia onset	77	62	92
Diplopia duration of transient attacks	**50**	**10**	**90**
Diplopia occurrence	63	46	81
Diplopia direction	**74**	**58**	**91**
Metamorphopsia	10	2	18
Metamorphopsia laterality	63	46	81
Metamorphopsia onset	60	42	78
Haloes around lights	2	0	5
Neurological symptoms	**1**	**0**	**3**
Temporal arteritis symptoms	**6**	**0**	**14**
Myasthenia gravis symptoms	**0**	**0**	**0**
Vomiting	0	0	0

Table 3.6. Percentage (with 95% confidence limits) of the expected additional problem orientated symptoms questions asked with respect to pain, photophobia, diplopia, metamorphopsia, haloes, and various symptoms of systemic disease. These estimates arose from manual searches of 224 "free text" fields. "Issue" questions are shown in bold.

Question	Percentage asked		
	%	95% confidence limits	
		lower	upper
Watery eye	43	26	61
Watery eye laterality	40	22	58
Watery eye occurrence – seasonal	0	0	0
Itchy eyes	29	16	41
Itchy eye laterality	40	22	58
Itchy eye occurrence – seasonal	7	0	16
Gritty eyes	6	0	13
Gritty eye laterality	10	0	21
Gritty eye occurrence – seasonal	0	0	0
Foreign body sensation	14	4	24
Foreign body sensation laterality	20	6	34
Foreign body sensation occurrence – seasonal	0	0	0
Reported red eye laterality	73	58	89
Reported red eye frequency – recurrent	23	8	38

Table 3.7. Percentage (with 95% confidence limits) of the expected additional problem orientated symptoms questions asked with respect to ocular surface irritation and red eye. These estimates arose from manual searches of 224 "free text" fields. "Issue" questions did not arise.

Question	Percentage asked		
	%	95% confidence limits	
		lower	upper
Patient ocular history - high myopia	2	0	5
Patient ocular history - head trauma	0	0	0
Patient ocular history – red eye with blurred vision	70	54	86
Patient ocular history – eye surgery	11	6	15
Patient medical history – allergies	20	9	32
Patient medical history – migraine	19	10	27
Patient medical history – recent cold	0	0	0
Patient medical history – systemic hypertension	22	15	28
Patient medical history – diabetes	24	16	32
Patient medical history – heart problems	7	2	11
Patient medical history – thyroid problems	7	0	16
Patient medical history– ankylosing spondylitis	0	0	0
Patient medical history – inflammatory bowel disease	0	0	0
Patient medical history – rheumatoid arthritis	1	0	4
Patient medical history – multiple sclerosis	0	0	0
Patient medical history – medication – eye drops	27	11	42
Patient medical history – medication – steroids	2	0	6
Family ocular history (parent or sibling) – macular degeneration	4	0	9
Family ocular history (parent or sibling) – retinal detachment	0	0	0
Family medical history (parent or sibling) – migraine	0	0	0
Family medical history (parent or sibling) – hayfever	0	0	0

Table 3.8. Percentage (with 95% confidence limits) of the expected additional problem orientated history questions. These estimates arose from manual searches of 224 "free text" fields. "Issue" questions did not arise.

Decision tree analysis was used to explore variations in the asking rates of different types of questions. The 105 questions were classified in terms of:

1. the eye examination style (Exam grouping) that they belonged to i.e. database style (database category), problem-orientated style (problem category) or both (mixed category);
2. whether or not they were "issue" questions (Issue grouping);
3. whether they belonged to (Focus grouping) a single symptom presentation class (one category) or several classes (many categories);

4. whether they related to (Description grouping) the reason for visit (RFV category), last eye examination (LEE category), last medical examination (LME category), visual demands (visual demand category), reduced vision (vision category), eye strain (asthenopia category), headaches (headache category), floaters (floaters category), photopsia (flashes category), irritation (irritation category), pain (pain category), photophobia (photophobia category), diplopia (diplopia category), haloes around lights (haloes category), neurological symptoms (neurological symptoms category), symptoms of temporal arteritis (TA symptoms category), symptoms of Myasthenia Gravis (MG symptoms category), reported vomiting (vomiting category), reported red eye (red eye category), patient ocular history (ocular history category), patient medical history (medical history category), family ocular or medical history (family history category) or any other symptoms (other symptoms category);
5. whether they related to location or laterality (L category), onset (O category), F (frequency category), type or severity (T category), effectiveness of self-treatment (S category), effect on patient (E category) and associated or secondary symptoms (A category) or neither (non LOFTSEA category), all of which were part of the LOFTSEA (LOFTSEA grouping) acronym taught at Aston (see section 1.3).

Percentage asking rates showed a statistically significant departure from a normal distributed (Kolmogorov-Smirnov Z = -1.527, p = 0.019) and required transformation. Being percentages, the arc sine transformation was carried out (Dr Richard Armstrong pers. comm. i.e. the arc sine of the square root of percentage value expressed as a proportion) to remove any statistically significant departure from a normal distributed (Kolmogorov-Smirnov Z = 0.898, p = 0.396). The decision tree analysis shown in Figure 3.1 was carried out with the transformed percentage asking rate of each of the 105 questions as the dependent variable and the groupings described above (Exam, Issue, Focus, Description and LOFTSEA) as independent variables.

Figure 3.1 shows that the symptoms and history questions taught at Aston were typically asked only about 20% of the time (see node 0 of the decision tree, 0.481 = 21%).

Asking rates were most influenced by the Description grouping ($F_{2,102} = 34.390$, $p < 0.0001$). The first set of branches (nodes 1 to 3) subdivided Description grouping categories into those with similar asking rates. A small group of questions (18%, see node 1) were typically asked about 60% of the time (0.868 = 58%) and included questions like reason for visit, floaters and flashes. The largest group of questions (61%, see node 2) were typically asked less than 10% (0.311 = 9%) of the time and, surprisingly, included all history questions. About 20% of the questions (21%, see node 3) were typically asked 36% (0.644 = 36%) of the time and included questions such as those covering visual demands and reduced vision.

Asking rates of the large group of questions asked least often (node 2) were influenced the Exam grouping ($F_{1,62} = 7.601$, $p = 0.008$, see nodes 4 and 5). Here it became apparent that database questions (including those that were also problem-orientated questions) were asked more often (typically 0.498 = 23% of the time, see node 4) than purely problem-orientated questions (typically 0.258 = 7% of the time, see node 5). This went some way to answer the third question posed in section 3.1; that is, for some questions, optometrists were more inclined to adopt database-style symptoms and history questions.

Asking rates for problem-orientated questions (node 5) were influenced by the LOFTSEA grouping ($F_{1,48} = 4.355$, $p = 0.042$, see nodes 6 and 7). Here questions covering onset (see node 7) was asked less often (typically about 0.126 = 2% of the time, see node 7) as questions such as those covering laterality and non LOFTSEA questions (typically about 0.300 = 9% of the time, see node 6).

The more frequently asked LOFTSEA and none LOFTSEA questions (node 6) were further influenced by the description grouping ($F_{1,36} = 14.483$, $p = 0.001$, see nodes 8 and 9). Here, questions relating to headaches, for example, were asked far more often (typically about 0.468 = 20% of the time, see node 8) than those covering symptoms of systemic disease (typically about 0.178 = 3% of the time, see node 8).

Neither of the Focus or Issue groupings had an influence on question asking rates. That the Issue grouping had no effect indicated that the anticipated difficulties in detecting “issue” questions (those shown in bold in Tables 3.4 to 3.8) had little impact on the findings.

Further scrutiny and interpretation of these findings adds little to this study but does serve to illustrate the types of questions that are typically not asked. The profession might find this information useful for Continuous Education and Training events aimed at improving practice.

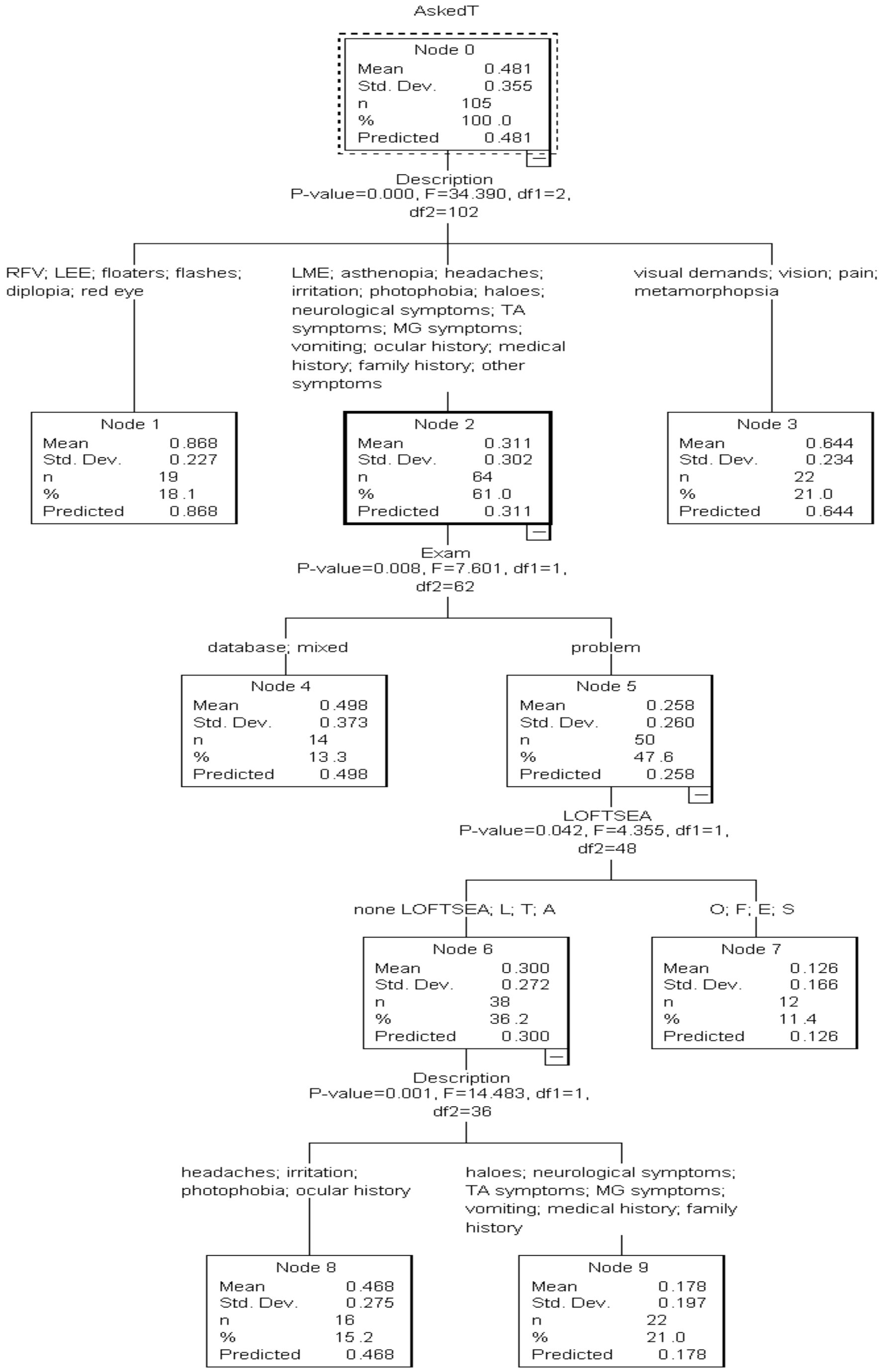

Figure 3.1. Decision tree analysis showing the dependence of transformed percentage asking rates (askedT) on 105 symptoms and history question classified in terms of Description, Exam and LOFTSEA groupings (see text). Asking rates were determined from manual searches through 224 records.

3.3.2 Does the conformity between what is taught and what is recorded vary for each presentation type?

Conformity was determined for all 224 records. It represented the percentage of expected questions actually asked and so was a measure of how well each record as a whole conformed to what Aston taught. Conformity showed no statistically significant departure from a normal distribution (Kolmogorov-Smirnov Z = 1.141, p = 0.148). Optometrists typically asked about a third of the expected questions (mean, 95% confidence limits and range: 32, 32 to 35, 6 to 73%). The second question posed in section 3.1, however, was how did conformity vary for each symptom presentation class?

Table 3.9 shows typical conformity levels in each symptom presentation class. The conformity of records for routine (asymptomatic) eye examinations had higher conformity (mean, 95% confidence limits: 46, 41 to 51%) than was found for those in which symptoms were reported (which ranged from 25 to 34%). The variation was statistically significant (One way ANOVA: $F_{10,358} = 8.944$, $p < 0.0001$).

			95% confidence limits	
Symptom presentation class	**N**	**mean**	lower	upper
Routine	30	46	41	51
Vision loss in white eye	50	29	27	31
Non traumatic red eye	30	29	25	32
Diplopia	30	30	26	33
Irritation (watery, itchy, gritty or FB sensation)	30	28	26	31
Floaters	30	34	31	37
Photopsia	36	32	29	35
Visual field loss	30	33	29	36
Metamorphopsia	30	29	25	34
Pain in or around eye	32	33	29	37
Headache	31	25	22	28

Table 3.9 Typical (mean and 95% confidence limits) conformity (the percentage of expected questions asked) for the 11 symptom presentation classes determined from manual searches on 224 records selected for this study. There were 30 to 50 records for each symptom presentation class. Some records contained multiple presenting symptoms and so the total of N comes to 359 rather than 224.

Rather than carry out post hoc comparisons between the conformity values of each symptom presentation class, it was considered that decision tree analysis (Figure 3.2) would be more informative. Decision tree analysis confirmed the statistically significant influence of symptom presentation class on percentage conformity ($F_{3,355} = 29.866$, $p < 0.0001$). It also confirmed that conformity was higher for routine (asymptomatic) examination records (45%, see node 4) and that the remaining symptom presentation classes formed three groups. Classes such as floaters and photopsia had the next highest conformity (typical conformity = 33%, see node 2). Next came classes including non-traumatic red eye and vision loss in white eye (typical conformity = 29%, see node 1) followed by the headache class exhibiting the lowest conformity levels (25%, see node 3).

Headache may have occupied the lowest class because Aston teaches its students to follow the MIPCA guidelines (see section 3.1) which may not be generally used in practice.

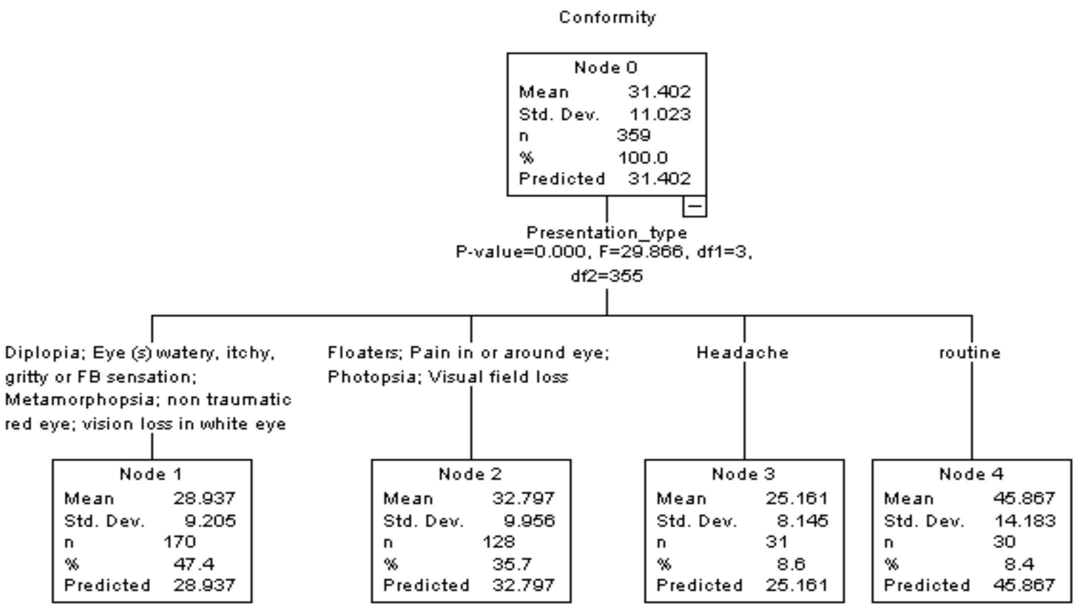

Figure 3.2. Decision tree analysis showing the dependence of conformity (the percentage of expected questions asked) on the 11 symptom presentation classes determined from manual searches on 224 records selected for this study. Some records contained multiple presenting symptoms and so the total sample was 359 rather than 224.

3.3.3 Do optometrists in multiple-practice typically adopt the database problem-orientated approach when recording symptoms and history?

This had already been partly answered in section 3.3.1 (see figure 3.1) which showed that optometrists tended to adopt a database style approach for certain types of questions; headache questions being one example. This aspect of the study was revisited by calculating, for each symptom presentation class, the average percentage asking rate for all database and problem-orientated style questions (Table 3.10).

The mean percentage asking rates shown in Table 3.10 showed no statistically significant departure from a normal distribution (Kolmogorov-Smirnov Z = 0.861, p = 0.448) and were consistently higher for database style questions compared to problem-orientated style questions (Paired t-test: t = 10.737, df = 9, P < 0.0001). Asking rates for the routine (asymptomatic) presentation class were not included in this comparison as they only included database style questions.

		Database			Problem-orientated		
			95% confidence limits			95% confidence limits	
	N	mean	lower	upper	mean	lower	upper
Routine	30	46	34	58	-	-	-
Vision loss in white eye	50	40	27	52	22	12	32
Non traumatic red eye	30	37	27	48	22	11	33
Diplopia	30	39	27	51	26	14	37
Irritation (watery, itchy, gritty or FB sensation)	30	38	27	49	22	13	32
Floaters	30	41	28	55	28	5	51
Photopsia	36	41	28	54	28	9	47
Visual field loss	30	40	28	52	29	17	42
Metamorphopsia	30	33	23	44	25	1	49
Pain in or around eye	32	40	29	51	33	17	49
Headache	31	38	26	49	19	7	31

Table 3.10. Typical (mean and 95% confidence limits) percentage asking rates for database and problem-orientated style questions in each of the 11 symptom presentation classes determined from manual searches on 224 records selected for this study. There were 30 to 50 records for each symptom presentation class. Some records contained multiple presenting symptoms and so the total of N comes to 359 rather than 224.

3.3.4 Regional variations

Decision tree analysis (Figure 3.3) was carried out to explore regional variations in percentage conformity (the percentage of expected questions asked) while taking account of the potentially confounding effect of the presenting symptoms that arose in each of the 224 records studied.

Figure 3.3 is so complicated that it is hard to see but led to the following key observations. The symptom presentation combinations influenced conformity most ($F_{3,220} = 15.324$, $p < 0.0001$). Symptom combinations were shown in brackets. For example "(..vision..field loss..headache..)" showed that reduced vision, visual field loss and headache coexisted in that record. Fifty-nine classes existed and it was considered pointless to attempt to interpret why these fell into 4 groups (nodes 1 to 4) because the purpose of this exercise was to account for symptom presentation combination as a confounding variable. All but one of these groups showed regional variations (node 1 - $F_{1,93} = 6.455$, $p = 0.013$; node 2 - $F_{1,26} = 5.622$, $p = 0.025$; node 4 - $F_{1,67} = 8.954$, $p = 0.004$) split in pairs such that one region had higher conformity than the other. Again, it was considered pointless to attempt to interpret these splits as the purpose of this exercise was only to demonstrate that regional variations existed. Previous studies that investigated the content of eye examinations using standardised patient methodology had taken data from only one region and, therefore, could not explore regional variations (section 1.4.1). The present study confirms that these exist. However, there appeared to be no consistency in the grouping shown in Figure 3.3. For example, it might be speculated that optometrist from the West Midlands area would have higher conformity scores as they may have been educated at Aston University. This was, however, not the case as West Midland optometrists had the lowest conformity in two out of three of the split pairs. Of course, it was not necessarily the case that the optometrists from the West Midlands were educated as Aston and the requirement for anonymised records meant that the author could not check this.

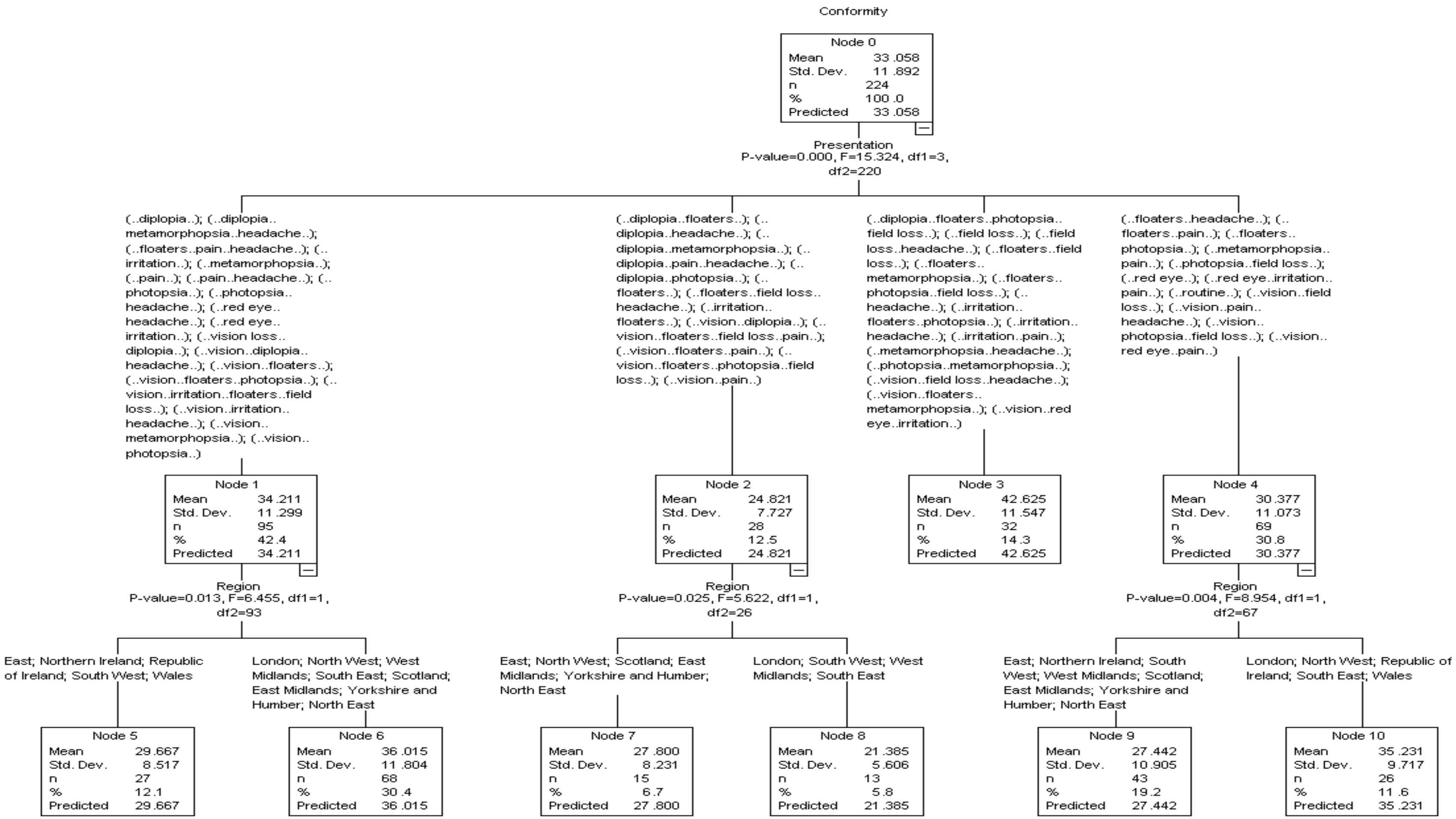

Figure 3.3. Decision tree analysis showing the dependence of conformity (the percentage of expected questions asked) on the one or more presenting symptoms that existed, determined from manual searches on 224 records selected for this studied, and the region of the United Kingdom from which each record was taken.

3.4 Summary

3.4.1 Key findings

The study described in this chapter involved detailed manual searches through 224 “free text” fields to determine how often optometrists asked 105 symptom and history test items taught at Aston University. Asking rates for individual questions varied from 0 to 88%. The proportion of expected questions asked in individual records (i.e. conformity) tended to be higher for eye examinations that were routine (no presenting symptoms: 95% confidence limits 41 to 51%) compared to those with presenting symptoms (the means for which ranged from 25 to 34%). Optometrists tended to ask database-style questions (mean asking rates varied from 33 to 40% depending on the presenting symptoms) more often than problem-orientated style questions (mean asking rates varied from 22 to 33% depending on the presenting symptoms). Decision tree analyses were used to explore the data in more depth and also showed statistically significant regional variations in conformity.

Aston’s teaching did not reflect what was asked in the multiple-practice setting. If Aston’s expectations were used for legal decisions, or as the basis of fitness to practice hearings then they would be entirely unrealistic. Adopting a conservative estimate, of possible use to the Association of Optometrists’ legal team, only 14% of questions taught by Aston were typically asked. Optometrists also only partially adopted efficient problem-orientated style questions to address presenting complaints.

These findings may not be cause for concern if optometrists rarely face medico-legal action on the basis of their recording of symptoms and history (i.e. the subjective element of SOAP). It could be that clinical test findings (i.e. the objective element of SOAP) tend to detect diseases of the visual system even if their presence is not picked up during symptoms and history. Nevertheless, Aston’s virtual patient is used in classes to illustrate that about 65% of its 255 cases can be diagnosed based on history and symptoms alone. Figures of above 80% have been quoted for medical practice. This raises the idea that algorithmic decision support systems designed to guide practitioners to more efficient lines of problem-orientated questioning have the potential to improve clinical practice and might even save chair time.

3.4.2 Study limitations

The key limitation to the study described in this chapter lay in its reliance on interpretation of "free text" symptoms and history fields which were frequently filled with inconsistent abbreviations and typographical errors. Had drop down menus been used instead then it would have been possible to extend this study from just 224 manually searched records to the larger sample of 5,944 records by means of electronic searches. The need for anonymization also meant that the author could not be certain that the 224 records represented 224 optometrists. Another limitation was the assumption that optometrists used the field made available to the author to record all symptoms and history items; though this was company policy and was confirmed by the professional services director.

It should also be noted that the teaching of history and symptoms questions in the format used by Aston is a relatively new method, introduced in 2010 and may not be reflected amongst older practitioners.

Chapter 4: Summary and recommendations for further research

4.1 Introduction

This chapter provides a discussion around the main findings of this study, including its limitations, and makes recommendations for further research.

4.2 Discussion around main findings

The findings of this study indicate that optometrists in community multiple practice do not obtain symptoms and history in the manner taught by Aston University. The hypothesis that optometrists do not ask as many questions as are taught at university was confirmed. It was shown that optometrists are more likely to ask database style questions (23%) rather than purely problem orientated (7%). The hypothesis that experienced optometrists conduct a more problem orientated examination was not confirmed, for symptoms and history at least.

In section 2.2.1 it was stated that only 44% of the original records remained after exclusion of those deemed unacceptable. Most exclusions were made on the basis that records fell outside the inter-quartile range of the record length. The purpose of exclusion based on length was to remove long records most likely written by pre-registration students and short records that may have been events such as follow up examinations. It was not possible to check however that, for example, the longer excluded records were those completed by pre-registration students. This is because the identity of optometrists, due to anonymisation, was unknown. This was another limitation of the study and further investigation is needed in order to determine how this may have biased the study findings.

Section 2.2.2 described the identification of search terms for presenting symptom types. This involved preliminary inspection of 1075 records by the author and returned 388 potentially useful terms. These initial searches may have benefitted from the input of focus groups made up of experienced optometrists. Unfortunately, however, there was no funding to allow this. Future research of this type should seek funds for focus group activity aimed at ensuring that the best possible search terms are chosen.

Questions such as a general (wide-ranging) enquiries regarding medications were asked between 88% and 96% (95% confidence limits) of the time. However, numerous questions that are taught by Aston University were not asked at all. Asking rates tended to be highest for routine presentations. This may be because for a routine patient the questions are all of a database style as there is no requirement for problem-orientated questions.

It was also found that of the questions that Aston University teaches, only 15 (14%) were asked more than 50% of the time, according to the lower 95% confidence interval. Eighty (79%) of the expected questions were typically asked less than 50% of the time and 18 (17%) of the questions were never asked.

Decision tree analysis showed that the asking rate of questions was most influenced by the description of the grouping. Questions such as reason for visit were asked approximately 60% of the time.

The author sought information on how other optometry schools in the UK taught history and symptoms. Responses were received from two schools indicating that database style eye examinations were taught early on in the course and problem-orientated style eye examinations were encouraged in later clinics. No further detail was received, suggesting that use of a standard list of history and symptom questions, for both eye examination styles, was not generally adopted in optometry schools. The plan is therefore, to publish the list used in the present study in order to seek general agreement across the profession on its contents.

It is not possible to tell if the findings from this study are linked to this particular multiple practice group or are indicative of optometric practice in general. As such this should be considered a limitation of the study. It is possible that the working environment of this practice group contributes to the questions that are not asked. To eliminate this as a possible factor the study would have to be repeated across other practice groups and record keeping systems. It is probable that the manner of recording employed by this practice management solution is directly linked to the way records are kept, and if this study was repeated in an environment that uses a different software system the findings may be very different.

If these findings are replicated across all optometry practices, then this has implications for the defense of practitioners at the GOC and against civil claims. The standard that is used at such hearings is that of the reasonable competent optometrist, with expert witnesses providing opinions on whether an optometrist would be expected to carry out a function.

With regard to symptoms and history the guidance provided by the College of Optometrists is used to inform this opinion. If the standard of symptoms and history taking and the questions asked is different to these guidelines, then the standard that is applied at the GOC and in civil claims may be inappropriate. It is important that practitioners facing allegations are judged against their peers and not against a gold standard, such as that taught at Aston University.

Recording procedures for anterior eye examinations were examined in a recent study (Wolffsohn et al., 2015a). The authors of his study investigated whether the use of word descriptions and grading scales within contact lens records had an impact upon the quality of the recording. It was noted that grading scales increased the reproducibility of grading, with the caveat that there was the potential for inaccuracies if practitioners used different grading scales or did not reference which scale they were using (Wolffsohn et al., 2015a). It would

seem that a more standardised approach improves reproducibility, but this could be detrimental to the practitioners, turning them from professionals into technicians.
The findings of this study may have been different had participating optometrists used record cards that contained question prompts. Questions that had been prompted will certainly have been asked more often. This was not the case for the present study in which optometrists entered their findings in completely empty text fields.

Non-compliance with clinical practice guidelines within a trauma triage setting has been examined in a previous study (Mohan et al., 2012). It was found that individual decision making led to deviation from defined clinical guidelines. It is difficult within a profession to remove the decision making of a professional, as it is this ability to make decisions that serves to define professionals rather than technicians. As such it is likely there will always be a divergence of actual practice from clinical guidance.

The use of stricter clinical practice guidelines could increase the number of questions that are asked. A question that this study has not addressed is does it cause harm to patients if these guidelines aren't followed? A separate piece of work would be required to retrospectively look at the number and type of questions asked versus the patient outcome, to determine if there was a link.

However, this poses the question of why would we wish to increase the number of questions that are asked. It has been asserted previously that database style eye examinations were used in training clinics and were designed to enable detection of most visual system diseases by students with limited clinical experience. This style of examination was, however, considered to be less suitable for qualified optometrists who had the experience to adopt more efficient problem-orientated eye examinations (Elliott, 2013).

Given the time pressures that optometrists face in their working day, it would appear that rather than asking questions in a database style as they currently do, there is a benefit to a more succinct problem-orientated style of questioning.

The study was also limited by the fact that optometry records often contain acronyms and abbreviations. Despite the College of Optometrist's guidance advising practitioners to only use recognised acronyms and abbreviations, many practitioners create their own version of shorthand. One way to deal with this problem would have been via text mining and making use of machine learning to automatically find key abbreviations. Machine learning algorithms are able to pick up specific language use, such as abbreviations and synonyms used by physicians (Schumeie et al., 2012). With increased resource and greater time, it would have been beneficial to build a robust form of machine learning to reduce the labour intensive stage of record analysis. This would have enabled the use of a greater sample size. Having said that, machines can only learn from pre-classified records which, as mentioned in chapter 2, is very time consuming.

It may be that as practitioners gain experience, they begin to adopt a more problem-orientated style. This could not be tested with the data that was used for this study due to the anonymisation process, which made it impossible to include level of experience as a factor. Steps were taken to remove the extremes during the sampling process by sampling from the middle two quartiles of the data, excluding extremely long and short records. It was theorized that the extremely long records were likely to be the records of pre-registration optometrists and as such were not reflective of standard practice. Many of the extremely short records appeared to have been created in error as they contained no useful information.

Regional variations were found to exist, but no meaningful pattern could be found. It seemed reasonable to postulate that those working in areas close to one of the optometry schools, and in particular those close to Aston University, may exhibit behavior that is closely aligned to the teachings at that particular university. However, this was not the case, with West Midlands optometrists having the lowest conformity in two out of three areas that were analysed. To resolve this issue, the study would need to gather demographic data on the optometrists. This would not only enable the measurement of the influence of university teaching on history and symptom taking, but also if there were any differences in age and sex.

4.3 Recommendations for further research

There is scope for further research that evaluates how practitioners of differing levels of experience conduct symptoms and history taking and whether there is any difference depending on the time since qualification. It would be interesting to determine if practitioners of differing experience are more inclined to adopt a problem orientated examination style.

Waikato Environment for Knowledge Analysis or WEKA is software for data and text mining. Unfortunately, this resource was not known to the author until just prior to the submission of this thesis. The following information is included as this software has potential for future research in this field.

WEKA is under continuing development at the University of Waikato in New Zealand and offers industry standard data and text mining facilities. It can be downloaded free of charge and runs in Windows, OSX and Linux. It can perform multinomial naïve Bayes which is particularly useful for text mining (McCallum & Nigam, 1998). Briefly, WEKA allows the user to upload a pre-classified set of text documents. It uses filters to split text documents into separate words prior to ranking these in terms of the information each term adds to the learning scheme. Only the most informative words are kept for machine learning using the multinomial naïve Bayes classifier. Stratified ten-fold cross-validation is carried out in order to determine the accuracy of the model (Kohavi, 1995). This commonly used method randomly splits the dataset into ten approximately equal parts (or folds) that are stratified so that each contains the same proportion of classes. Each part is used in turn for testing and the remainder is used for training. The process is repeated ten times so that every text document has been used once for testing. Errors arising for each run are then averaged to give an estimate of predicted accuracy.

Felipe et al. (2015) utilized WEKA for automated analyses of twitter to gauge public opinion on various matters. Antti (2015) demonstrated that WEKA offered a scalable text mining solution to learning from big data. WEKA can achieve this using its updateable learning schemes, including naïve Bayes. These operate by learning from one record at a time before and then discarding the record having updated the learning scheme. Because the computer only has to hold the learning rules and one record in its memory, even desktop computers with modest memory can process web-based datasets of unlimited size (Witten et al., 2011).

A limitation of WEKA is that it can only handle single-label data. That is, it could classify a text document as having one of a number of alternative characteristics. The problem addressed in this thesis is to determine whether multiple characteristics are present in each text document. WEKA could tackle this by running the learning scheme many times in which each run targets a different characteristic. Another solution would be to adopt MEKA in which M stands for multiple. This software is based upon WEKA and permits multi-label learning; in which multiple characteristics are targeted simultaneously.

Neither WEKA or MEKA are able to overcome the huge task of classifying text documents in the first place. This has to be done manually by a human observer. While it would have been desirable to use WEKA or MEKA, naïve Bayes applied in the manner adopted previously at Aston University by Sagar (2014) could achieve the thesis objectives just as well. Indeed, Witten et al. (2011), who provide excellent background information and tutorials on the use of WEKA, were great advocates of simplicity.

In the work by Shah et al. (2009), it was suggested that use of computerised optometric recording systems would increase the false positives and false negatives in data collected by record abstraction. This is because the ease with which commonly used clinical findings can be selected from drop down menus (increasing false positives), and because of the extra time required to type all of the patients' responses into text boxes (increasing false negatives). As the data analysed in the present study had been typed into text boxes that lack drop down menus then the results are likely to contain very few false positives. False negatives were, however, likely to remain. This drawback was of little importance to this study, given that it was the recording habits of the typical optometrist that were of interest. However, it does act as a counter argument to the idea that using a computersied system is capable of improving the quality of record keeping. It would appear that careful consideration should be given to how a system is used to avoid the problems of false positives; this should be incorporated into any further work in this area.

Further work should also include the investigation of whether there was scope for the future use of diagnostic support systems containing algorithms, similar to those used by the Virtual Patient, to prompt for the under-used problem-orientated questions that could make more efficient diagnoses. It is possible these algorithms could be made simple enough for patients to use while waiting for an eye examination, maybe with some help from the optical assistants. If this process could be proven to be effective, there is potential for both improved diagnostic accuracy and also a time saving on the length of symptoms and history taking, allowing more time for other tests that may be indicated. The findings of this research project could potentially inform the development of diagnostic support systems by comparing the efficacy of diagnosis, based on history and symptoms alone, using an ideal question set versus questions typically asked. This could be a fruitful avenue of research in the future and offers the possibility of developing online and tablet based diagnostic support systems that could be used by clients when booking eye examinations or waiting in the reception area for an eye examination.

No attempt was made, using the Virtual Patient, to determine how many questions were needed to confirm each diagnosis. This was not considered useful for the analyses of the present study but could be useful for determining the feasibility of an online triage system that patients use when booking eye examinations. Future research may explore the potential for such a system. This study could, in the future, be extended to other health professionals consulted about eye problems, such as pharmacists and general practitioners. Maybe online or tablet based diagnostic support systems could be developed for use by the clients of these professionals as well. The implications of technology such as this needs to be carefully considered to avoid reducing the role of the optometrist to that of a technician. There could be profound implications for the profession if technological solutions are not carefully monitored.

References

Abdullah, S. S., Rahaman, M. S., & Rahman, M. S. (2013, May). Analysis of stock market using text mining and natural language processing. In *Informatics, Electronics & Vision (ICIEV), 2013 International Conference on* (pp. 1-6). IEEE.

Altman, D. G., & Bland, J. M. (1994). Diagnostic tests. 1: Sensitivity and specificity. *BMJ: British Medical Journal*, *308*(6943), 1552.

Ashby, D., & Smith, A. F. (2000). Evidence-based medicine as Bayesian decision-making. *Statistics in medicine*, *19*(23), 3291-3305.

Ashby, D. (2006). Bayesian statistics in medicine: a 25 year review. *Statistics in medicine*, *25*(21), 3589-3631.

Aspinall, P., & Hill, A. R. (1983). Clinical inferences and decisions—I. Diagnosis and Bayes‘ theorem. *Ophthalmic and Physiological Optics*, *3*(3), 295-304.

Balasubramanian, A., & Jawahar, C. V. (2006). Textual search in graphics stream of PDF. In *International conference on digital libraries* (pp. 1-10).

Ball, G. V. (1982). *Symptoms in eye examination*. Butterworth-Heinemann.

Bauer, M. W., Bicquelet, A., & Suerdem, A. K. (2014). Text analysis: An introductory manifesto.

Mr. Bayes, & Price, M. (1763). An essay towards solving a problem in the doctrine of chances. by the late rev. mr. bayes, frs communicated by mr. price, in a letter to john canton, amfrs. *Philosophical Transactions (1683-1775)*, 370-418

Bezan, D. J., Larussa, F. P., Nishimoto, J. H., Sendrowski, D. P., Spear, C. H., Talley, D. K., & Than, T. P. (1998). Differential diagnosis in primary eye care.

Bijalwan, V., Kumari, P., Pascual, J., & Semwal, V. B. (2014). Machine learning approach for text and document mining. *arXiv preprint arXiv:1406.1580*.

Bar-Hillel, M. (1980). The base-rate fallacy in probability judgments. *Acta Psychologica*, *44*(3), 211-233.

Breiman, L., Friedman, J., Stone, C. J., & Olshen, R. A. (1984). *Classification and regression trees*. CRC press.

Brain, S., & Page, L. (1998). The anatomy of a large scale hypertextual web search engines. *Computer Networks and ISDN System30 (1-7)*, 107-117.

Bravo-Marquez, F., Frank, E., & Pfahringer, B. (2015, August). From unlabelled tweets to Twitter-specific opinion words. In *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp. 743-746). ACM.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge university press.

Carpenter, I., Ram, M. B., Croft, G. P., & Williams, J. G. (2007). Medical records and record-keeping standards. *Clinical Medicine*, *7*(4), 328-331.

Cios, K. J., & Moore, G. W. (2002). Uniqueness of medical data mining. *Artificial intelligence in medicine*, *26*(1), 1-24.

The College of Optometrists. (2015) Welcome to the Guidance for Professional Practice. Available online at: http://guidance.college-optometrists.org/home/ (accessed December 2015)

Dahm, M. F., & Wadensten, B. (2008). Nurses' experiences of and opinions about using standardised care plans in electronic health records–a questionnaire study. *Journal of Clinical Nursing*, *17*(16), 2137-2145.

DOCET, (2009) On the Record –good practice in record keeping. docet.pixl8-hosting.co.uk/download.cfm?docid=18AA6254-37B5.Cached

Dresselhaus, T. R., Peabody, J. W., Lee, M., Wang, M. M., & Luck, J. (2000). Measuring compliance with preventive care guidelines. *Journal of General Internal Medicine*, *15*(11), 782-788.

Dunstone, D., Armstrong, R., & Dunne, M. (2013). Survey of habits and attitudes to retinoscopy by optometrists in the UK. *Optometry*, *14*(2).

Frank, E., Mayo, M., & Kramer, S. (2015, April). Alternating model trees. In *Proceedings of the 30th Annual ACM Symposium on Applied Computing* (pp. 871-878). ACM.

Elliott, D. B. (2013). *Clinical procedures in primary eye care*. Elsevier Health Sciences.

Evans, S. C., Roberts, M. C., Keeley, J. W., Blossom, J. B., Amaro, C. M., Garcia, A. M., ... & Reed, G. M. (2015). Vignette methodologies for studying clinicians' decision-making: Validity, utility, and application in ICD-11 field studies. *International Journal of Clinical and Health Psychology*, *15*(2), 160-170.

Fenton, N., & Neil, M. (2010). Comparing risks of alternative medical diagnosis using Bayesian arguments. *Journal of Biomedical Informatics*, *43*(4), 485-495.

Ferrante, J. M., Ohman-Strickland, P., Hahn, K. A., Hudson, S. V., Shaw, E. K., Crosson, J. C., & Crabtree, B. F. (2008). Self-report versus medical records for assessing cancer-preventive services delivery. *Cancer Epidemiology Biomarkers & Prevention*, *17*(11), 2987-2994.

Frank, E., Paynter, G. W., Witten, I. H., Gutwin, C., & Nevill-Manning, C. G. (1999). Domain-specific keyphrase extraction.

General Optical Council (2014) GOC Annual report 2013-2014

General Optical Council (2015) Code of Conduct

Gill, C. J., Sabin, L., & Schmid, C. H. (2005). Why clinicians are natural bayesians. *BMJ-British Medical Journal-International Edition*, *330*(7499), 1080-1083.

Graesser, A. C., Singer, M., & Trabasso, T. (1994). Constructing inferences during narrative text comprehension. *Psychological review*, *101*(3), 371.

Gu, Y., Storey, V. C., & Woo, C. C. (2015, October). Conceptual Modeling for Financial Investment with Text Mining. In *International Conference on Conceptual Modeling* (pp. 528-535). Springer International Publishing.

Guillon, M., & Maissa, C. (2005). Dry eye symptomatology of soft contact lens wearers and nonwearers. *Optometry & Vision Science*, *82*(9), 829-834. Chicago.

Hamilton, W. T., Round, A. P., Sharp, D., & Peters, T. J. (2003). The quality of record keeping in primary care: a comparison of computerised, paper and hybrid systems. *Br J Gen Pract*, *53*(497), 929-933.

Hampton, J. R., Harrison, M. J., Mitchell, J. R., Prichard, J. S., & Seymour, C. (1975). Relative contributions of history-taking, physical examination, and laboratory investigation to diagnosis and management of medical outpatients. *Br Med J*, *2*(5969), 486-489.

Hand, D. J. (1998). Data mining: statistics and more?. *The American Statistician*, *52*(2), 112-118.

Hanumanthappa, M., & Swamy, M. N. (2014). A Detailed Study on Indian Languages Text Mining.

Hearst, M. (2003). What is text mining. *SIMS, UC Berkeley*.

Hotho, A., Nürnberger, A., & Paaß, G. (2005). A Brief Survey of Text Mining. In Ldv Forum (Vol. 20, No. 1, pp. 19-62).

Inkpen, D. (2016). Text Mining in Social Media for Security Threats. In *Recent Advances in Computational Intelligence in Defense and Security* (pp. 491-517). Springer International Publishing.
Inmon, B. (2006). DW 2.0; Architecture for the Next Generation of Data Warehousing. *Information Management*, *16*(4), 8.

Inmon, W. H. (2006). Matching unstructured data and structured data. *The data administration newsletter*.

Jackson TL (2014) Moorfields manual of ophthalmology. Mosby Elsevier, Philadelphia.Data Mining and Visualization Silicon Graphics Inc.

Johnson, F., & Gupta, S. K. (2012). Web Content Mining Techniques: A Survey. International Journal of Computer Application. Volume 47, (11), p44.

Jones, J. W. (2000). Law & ethics: The healthcare professional and the Bolam test. *British dental journal*, *188*(5), 237-240.
Jones S, (1992) Was there a Hawthorne Effect?, Am j Sociol 98:451468

Kim, J. D., Ohta, T., Tsuruoka, Y., Tateisi, Y., & Collier, N. (2004, August). Introduction to the bio-entity recognition task at JNLPBA. In *Proceedings of the international joint workshop on natural language processing in biomedicine and its applications* (pp. 70-75). Association for Computational Linguistics.

Kohavi, R. (1996, August). Scaling Up the Accuracy of Naive-Bayes Classifiers: A Decision-Tree Hybrid. In *KDD* (Vol. 96, pp. 202-207).

Koster, C. H. A., Seutter, M., & Beney, J. (2001). Classifying patent applications with winnow.

Kulkarni, A., & Callan, J. (2008, June). Dictionary definitions based homograph identification using a generative hierarchical model. In *Proceedings of the 46th Annual Meeting of the Association for Computational Linguistics on Human Language Technologies: Short Papers* (pp. 85-88). Association for Computational Linguistics.

Li, R. Y. M. (2015). Relevant Data in the Rising Tide of Big Data: A Text-Mining Analysis in Construction Safety Index. In *Construction Safety and Waste Management* (pp. 61-73). Springer International Publishing.

Loewenstein, J. I., & Lee, S. (Eds.). (2004). *Ophthalmology: Just the facts*. McGraw-Hill.

Macalister, G., & Wickham, L. (2008). Clinical Decision Making VI: Diagnosis of Visual loss; Posterior Segment. *Optometry Today*, *48*(24), 28-37.

Martin, B. (1995). Instance-based learning: nearest neighbour with generalisation.

Maynard, D., Bontcheva, K., & Rout, D. (2012). Challenges in developing opinion mining tools for social media. *Proceedings of the@ NLP can u tag# usergeneratedcontent*, 15-22.

McCallum, A., & Nigam, K. (1998, July). A comparison of event models for naive bayes text classification. In *AAAI-98 workshop on learning for text categorization* (Vol. 752, pp. 41-48).

McCarney, R., Warner, J., Iliffe, S., Van Haselen, R., Griffin, M., & Fisher, P. (2007). The Hawthorne Effect: a randomised, controlled trial. *BMC medical research methodology*, *7*(1), 1.

Wainer, H. (2012). The Theory That Would Not Die: How Bayes' Rule Cracked the Enigma Code, Hunted Down Russian Submarines and Emerged Triumphant from Two Centuries of Controversy. by McGrayne, Sharon Bertsch.

Medelyan, O., & Witten, I. H. (2008). Domain-independent automatic keyphrase indexing with small training sets. *Journal of the American Society for Information Science and Technology*, *59*(7), 1026-1040.

Michelakis, E., Androutsopoulos, I., Paliouras, G., Sakkis, G., & Stamatopoulos, P. (2004). Filtron: A learning-based anti-spam filter. In *proceedings of the 1st conference on email and anti-spam. Mountain*.

Mitchell, T. M. (1997). Machine learning. WCB.

Mohan, D., Rosengart, M. R., Farris, C., Fischhoff, B., Angus, D. C., & Barnato, A. E. (2012). Sources of non-compliance with clinical practice guidelines in trauma triage: a decision science study. *Implementation Science*, *7*(1), 1.

OED Online. Oxford University Press, December 2015. Web. 14 January 2016.

Optical Confederation (2014) Optics at a Glance.

Ordenes, F. V., Theodoulidis, B., Burton, J., Gruber, T., & Zaki, M. (2014). Analyzing Customer Experience Feedback Using Text Mining A Linguistics-Based Approach. *Journal of Service Research*, 1094670514524625.

Paaß, G. (2005). H. deVries. Evaluating the performance of text mining systems on real. world press archives. In Proc. 29th Annual Conference of the German Classification Society (GfKl 2005). Springer.

Pan, L., Fergusson, D., Schweitzer, I., & Hebert, P. C. (2005). Ensuring high accuracy of data abstracted from patient charts: the use of a standardized medical record as a training tool. *Journal of clinical epidemiology*, *58*(9), 918-923.

Pane, A., & Simcock, P. (2005). *Practical ophthalmology: a survival guide for doctors and optometrists*. Elsevier Health Sciences.

Parikh, R., Parikh, S., Arun, E., & Thomas, R. (2009). Likelihood ratios: clinical application in day-to-day practice. *Indian journal of ophthalmology*, *57*(3), 217.

Paudel, P., Cronjé, S., O'Connor, P. M., Rao, G. N., & Holden, B. A. (2014). Selection considerations when using a 'standard optometrist'to evaluate clinical performance of other eye-care personnel. *Clinical and Experimental Optometry*, *97*(5), 426-432.

Paulsen, A. J., Cruickshanks, K. J., Fischer, M. E., Huang, G. H., Klein, B. E., Klein, R., & Dalton, D. S. (2014). Dry eye in the beaver dam offspring study: prevalence, risk factors, and health-related quality of life. *American journal of ophthalmology*, *157*(4), 799-806.

Pierscionek, B. K. (2008). *Law and ethics for the eye-care professional*. Butterworth Heinemann/Elsevier.

Quinlan, J. R. (1986). Induction of decision trees. *Machine learning*, *1*(1), 81-106.

Rebholz-Schuhmann, D., Oellrich, A., & Hoehndorf, R. (2012). Text-mining solutions for biomedical research: enabling integrative biology. *Nature Reviews Genetics*, *13*(12), 829-839.

Restrepo, N. A., Farber-Eger, E., Goodloe, R., Haines, J. L., & Crawford, D. C. (2015). Extracting primary open-angle glaucoma from electronic medical records for genetic association studies. *PloS one*, *10*(6), e0127817.

Ridgman, W. J. (1975). *Experimentation in biology*. Blackie.

Roy, S. C., Faulkner, G., & Finlay, S. J. (2007, September). Hard or soft searching? Electronic database versus hand searching in media research. In *Forum Qualitative Sozialforschung/Forum: Qualitative Social Research* (Vol. 8, No. 3).

Rubini, P., & Leela, M. S. (2013). A SURVEY ON PLAGIARISM DETECTION IN TEXT MINING. *International Journal of Research in Computer Applications and Robotics*, *1*, 117.

Rushton, R. M., Armstrong, R. A., & Dunne, M. (2016). The influence on unaided vision of age, pupil diameter and sphero-cylindrical refractive error. *Clinical and Experimental Optometry*.

Sallustio, B. (2008). Clinical Decision Making II: The Painful Eye. *Optometry Today*, *48*(16), 30-38.

Sagar, R. (2014). *Application of Naïve Bayesian sequential analysis to primary care optometry* (Doctoral dissertation, Aston University).

Schuemie, M. J., Sen, E., t Jong, G. W., Soest, E. M., Sturkenboom, M. C., & Kors, J. A. (2012). Automating classification of free-text electronic health records for epidemiological studies. *Pharmacoepidemiology and drug safety*, *21*(6), 651-658.

Sebastiani, F. (2002). Machine learning in automated text categorization. *ACM computing surveys (CSUR)*, *34*(1), 1-47.

Shah, R., Edgar, D., & Evans, B. J. (2007). Measuring clinical practice. *Ophthalmic and Physiological Optics*, *27*(2), 113-125.

Shah, R., Edgar, D. F., Rabbetts, R., Blakeney, S. L., Charlesworth, P., Harle, D. E., & Evans, B. J. (2008). The content of optometric eye examinations for a young myope with headaches. *Ophthalmic and Physiological Optics*, *28*(5), 404-421.

Shah, R., Edgar, D. F., Harle, D. E., Weddell, L., Austen, D. P., Burghardt, D., & Evans, B. J. (2009). The content of optometric eye examinations for a presbyopic patient presenting with symptoms of flashing lights. *Ophthalmic and Physiological Optics*, *29*(2), 105-126.

Shah, R., Edgar, D. F., Spry, P. G., Harper, R. A., Kotecha, A., Rughani, S., & Evans, B. J. (2009). Glaucoma detection: the content of optometric eye examinations for a presbyopic patient of African racial descent. *British Journal of Ophthalmology*, *93*(4), 492-496.

Shah, R., Edgar, D. F., & Evans, B. J. (2009). How well does record abstraction quantify the content of optometric eye examinations in the UK?. *Ophthalmic and Physiological Optics*, *29*(4), 383-396.

Shah, R., Edgar, D. F., & Evans, B. J. (2010). A comparison of standardised patients, record abstraction and clinical vignettes for the purpose of measuring clinical practice. *Ophthalmic and Physiological Optics*, *30*(3), 209-224.

Singh, K., Smiddy, W. E., & Lee, A. G. (Eds.). (2002). *Ophthalmology review: a case-study approach*. Thieme.

Singh, M. P. (Ed.). (2004). *The practical handbook of internet computing*. CRC Press.

Suarez-Tangil, G., Tapiador, J. E., Peris-Lopez, P., & Blasco, J. (2014). Dendroid: A text mining approach to analyzing and classifying code structures in android malware families. *Expert Systems with Applications*, *41*(4), 1104-1117.

Subarani, D. (2012). Concept Based Information Retrieval from Text Documents. *Dept. of Computer Sciences, SLN College of Sciences, Tirupathi, India, IOSR Journal of Computer Engineering (IOSRJCE)*, 38-38.

Tan, A. H. (1999, April). Text mining: The state of the art and the challenges. In *Proceedings of the PAKDD 1999 Workshop on Knowledge Disocovery from Advanced Databases* (Vol. 8, pp. 65-70).

Theodossiades, J., Myint, J., Murdoch, I. E., Edgar, D. F., & Lawrenson, J. G. (2012). Does optometrists' self-reported practice in glaucoma detection predict actual practice as determined by standardised patients?. *Ophthalmic and Physiological Optics*, *32*(3), 234-241.

Turney, P. (1999). *Learning to extract key phrases from text, ERB-1057*. Ottawa, ON, Canada, National Research Council of Canada, Institute for Information Technology, 1999: 1-43.

Vijayarani, S., Ilamathi, M. J., & Nithya, M. Preprocessing Techniques for Text Mining-An Overview. *vol*, *5*, 7-16.

Warburton, T. (2008). Staying out of trouble–Will your record keeping help or hinder?. *Optom Today*, *48*, 40-42.

Warburton, T. (2004). Litigation and record keeping. *Optom. Today*, *44*, 20-23.

Warburton T. (2006) Remember to carry out your work properly, or not at all. Optom Today, 46, 20.

Williams, S. E., Carnahan, R., & McPheeters, M. L. (2013). A systematic review of validated methods for identifying uveitis using administrative or claims data. *Vaccine*, *31*, K88-K97.

Witten, I. H., & Frank, E. (2005). *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann.

Wolffsohn, J. S., Naroo, S. A., Christie, C., Morris, J., Conway, R., & Maldonado-Codina, C. (2015). Anterior eye health recording. *Contact Lens and Anterior Eye*, *38*(4), 266-271.

Wolffsohn, J. S., Naroo, S. A., Christie, C., Morris, J., Conway, R., Maldonado-Codina, C., ... & of Contact, T. B. U. C. (2015). History and symptom taking in contact lens fitting and aftercare. *Contact Lens and Anterior Eye*, *38*(4), 258-265.

Yu, L., Zheng, J., Shen, W. C., Wu, B., Wang, B., Qian, L., & Zhang, B. R. (2012, August). BC-PDM: data mining, social network analysis and text mining system based on cloud computing. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 1496-1499). ACM.

Zaki, M., & Theodoulidis, B. (2013). Analyzing Financial Fraud Cases Using a Linguistics-Based Text Mining Approach. *Available at SSRN 2353834*.

Zhu, F., Patumcharoenpol, P., Zhang, C., Yang, Y., Chan, J., Meechai, A., ... & Shen, B. (2013). Biomedical text mining and its applications in cancer research. *Journal of biomedical informatics*, *46*(2), 200-211.