British Journal of Ophthalmology

The application of real-time artificial intelligence to cataract surgery

Journal:	*British Journal of Ophthalmology*
Manuscript ID	bjo-2024-326111.R2
Article Type:	Clinical science
Date Submitted by the Author:	n/a
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Keywords:	Medical Education, Lens and zonules, Ophthalmologic Surgical Procedures, Public health, Surgeons

Title

The application of real-time artificial intelligence to cataract surgery – *Authors*

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Synopsis/Precis (33/35 words)

This study demonstrates the first use of an AI system for analysing efficiency metrics in live cataract surgery. Results demonstrate that real-time AI has potential to improve operative efficiency and surgical team training.

Key Messages

What is already known on this topic – *summarise the state of scientific knowledge on this subject before you did your study and why this study needed to be done*

Recent concerted efforts provide technological solutions to accelerate ophthalmic surgical learning curves but not increasing operational efficiency. Artificial evidence (AI) is increasingly being utilised in ophthalmology, however sparsely utilised in ophthalmic surgery. Other specialities have also demonstrated the value of real-time AI in improving procedural quality and efficiency. This study was conducted to evaluate the benefit of AI in improving operative efficiency.

What this study adds – *summarise what we now know as a result of this study that we did not know before*

We have demonstrated the research application of a novel AI phase detection and real-time auxiliary screen system designed for use in real-time cataract surgery. The validity of these tools has been demonstrated, in addition to their potential to increase operative efficiency.

How this study might affect research, practice or policy - *summarise the implications of this study*

Real-time AI, with the use of auxiliary screens, has the potential to reduce surgical inefficiencies and support a fundamentally different and more efficient cataract surgical theatre of the future. With waiting lists for routine surgery ever increasing and as pressure increases on public health systems globally, this technology may be utilised to meet increasing demand.

The deployment of AI-based phase detection to cataract surgery also opens the door to a new era of surgical data analysis and enables clinicians for the first time to perform detailed observational studies in order to answer scientific questions about optimal surgical technique and increase efficiency.

Abstract

Background/Aims

Artificial intelligence (AI) in Ophthalmology has yet been applied to real-time cataract surgery. This work explores a new AI tool, developed for phacoemulsification and evaluates its potential uses.

Firstly, our study aimed to demonstrate the use of AI in phase recognition and analysis of phacoemulsification. Secondly, to evaluate application of real-time AI to live cataract surgery.

Methods

Phase I: Surgical video recordings of adult patients undergoing cataract surgery at Moorfields Eye Hospital were captured. The AI, via Touch Surgery^{TM} Ecosystem, was developed and used to segment surgery into phases based on the ICO-OSCAR Tool.

Phase II: Having demonstrated the AI’s functionality in phase I, a further group of phacoemulsification patients were recruited into a live surgery study arm. Three auxiliary screens were deployed in the operating theatres, displaying phase detection and phase relevant information in real-time.

Results

Phase I: 192 videos were analysed between March 2020 and March 2021. Average case duration for consultants (n = 68), advanced trainees (n = 59) and junior trainees (n = 65) was 11:18, 17:54 and 21:36 minutes respectively. Efficiency benchmarks were determined using the median metric values for advanced trainee and consultant cases, respectively.

Phase II: Efficiency metrics for 74 cases with screen deployment and 26 without were compared. With real-time AI, consultant surgeons had a significant decrease in case duration.

Conclusions

We demonstrate the first use of a fully independent AI platform for analysing efficiency metrics in cataract surgery. Real-time AI has potential to improve operative efficiency and surgical team training.

Manuscript

Introduction

There has been a proliferation in the application of artificial intelligence (AI) in healthcare and this was one of the central pillars of the Topol Review [1], laying out a vision for technologies to benefit patients. AI deployment has begun in a number of healthcare specialties but there are a number of technical, ethical and practical challenges [2, 3]. AI requires large volumes of data to be trained and operate successfully. This data needs to be carefully processed, frequently by a human, in the training process. In ophthalmology, much of the AI work thus far has focused on the retina (including diabetic retinopathy [4] and macular degeneration), OCT imaging and visual field analysis [5].

In cataract surgery, headway has been made in the application of AI to biometric formulae, intraocular lens optimisation and the diagnosis of cataracts. However, additional challenges arise when aiming to apply AI to video analysis and live scenarios [6]. Little work has been done to harness the power of the rapidly evolving field of real-time AI [7], particularly to improve operative efficiency in cataract surgery. Surgical operative efficiency is multi-factorial, defined by time (including surgical procedure time) and maximising utilisation.

There is an ever-growing pressure to increase throughput in operating lists due to clinical waits being longer than ever, exacerbated by the Covid-19 pandemic [8]. This is coupled with safety standards being higher than before and the parallel need for training. Technological deployment and AI specifically, has the potential to tackle the aforementioned challenges; the first being able to demonstrate that such a system can work.

In this work, Moorfields Eye Hospital (MEH) collaborated with Medtronic to utilise their Touch Surgery™ Ecosystem (TSE) to evaluate the application of AI in cataract surgery. This builds upon existing work of machine learning in cataract and other ophthalmic surgery (demonstrating that non-automated and non-fully independent algorithms can track surgical phases), training paradigms (for internationally agreed segmentation of the phacoemulsification operation) and validated metrics [9, 10] (showing that time, instrument movement, camera centration and other metrics are good discriminators of experience).

This proof-of-concept study aims to evaluate this AI tool and demonstrate its utility in cataract surgery.

Materials and Methods

Full IRB and ethics approval were awarded for this study (REC: 14/WM/0038).

Patient recruitment

All adult patients (aged 18-100) attending for routine cataract surgery at nine MEH sites across London, UK, were prospectively invited to participate, consented then enrolled in the study. Additional consent was obtained for Phase II of the study, where patients agreed for their information to be collected in addition to the surgical video. Exclusion criteria included concurrent pathology that precluded an adequate view of the surgery through the recording apparatus (e.g. extensive corneal scarring), concurrent procedures being performed simultaneously (e.g. iStent insertion) and patients unable to give consent.

The clinical pathway continued as normal with each patient's phacoemulsification operation being recorded through the operating microscope using standard operating theatre equipment. The video was then uploaded to TSE, an AI-powered surgical video management and analytics platform provided by Medtronic.

Phase I

To provide an effective comparator for the performance of the AI tool being developed, we used the template of previous work undertaken at MEH [9] and the International Council of Ophthalmology (ICO-OSCAR) [11]. The Machine Learning (ML) work has previously compared junior and senior surgeons and their efficiencies and metrics; their validated results were used in the stratification applied in this study. Similarly, the validated ICO-OSCAR tool [11] segmented cataract surgery is based on internationally agreed and published weightings; these were used to inform and train the AI system to replicate the segmentation.

The AI was then trained to recognise the same phase definitions and the surgeon grading was kept consistent with previously published work (see section below). We aimed to evaluate the performance of the AI by asking it to examine timings of each phase, for each grade of surgeon, in each video.

The algorithm of this AI differs fundamentally to any previous work; it is fully automated, has been engineered for full operational deployment (rather than simply to differentiate surgical grade) and can be upscaled (see discussion).

Workflow analysis and segmentation of the cataract surgery

TSE AI segmented the case recordings into surgical phases, defined using the internationally validated framework devised for the International Council of Ophthalmology: The ICO-Ophthalmology Surgical Competency Assessment Rubric: Phacoemulsification [11] (ICO-OSCAR: Phaco). This was further defined by interviews with clinicians. Qualified annotators, trained on surgically validated guidelines, quality-assured the AI-generated annotations to ensure consistency and accuracy.

The surgical phases were as follows: Preparation, Paracentesis, Main Port incision, Application of Viscoelastic, Capsulorhexis, Hydrodissection and Lens Mobilisation, Phacoemulsification, Irrigation and Aspiration, Re-application of Viscoelastic, Intraocular Lens (IOL) Insertion, Viscous Agent Removal, and Wound Closure.

Following segmentation of each surgery into the above phases, the sequence of phases completed, duration of each phase of surgery and the duration of the operation were analysed. Cases were defined as incomplete and excluded from further analysis if any of the following phases were missing: Paracentesis, Main Port Incision, Application of Viscoelastic, Capsulorhexis, Hydrodissection and Lens Mobilisation, Phacoemulsification, Irrigation and Aspiration, Re-application of Viscoelastic and IOL Insertion. As preparation and wound closure phases were not consistently recorded across the datasets, they were excluded from the analysis for consistency. Comparisons were then made between the surgeons in each of the cohorts based on experience.

Surgical grade stratification aligning with previously published work

Surgeons operating on patients who had enrolled in the study were themselves prospectively recruited into the study and divided into cohorts based on experience. A junior trainee surgeon was defined as an operator with under 100 completed cases, advanced trainee surgeon between 100-1000 and consultant (attending) surgeon with over 1000 completed cases [9].

Artificial Intelligence (AI) algorithm and analytics

The automatic annotation of captured videos uploaded to TSE was performed using an algorithm that has been reported previously [12]. The algorithm identifies the phases mentioned above, with 93.7% accuracy [13]. The algorithm was built by deframing videos at 1 frame per second and separated into training (80%), validation (10%) and testing sets (10%). In order to automatically analyse the videos, Convolutional Neural Networks (CNN) architectures were trained to classify individual frames. Since a single frame is not sufficient to understand the phase of the operation, the feature outputs of the CNN networks were then fed into a Temporal Convolutional Network to improve temporal consistency, as described previously by others [12, 13].

A subset of videos was also analysed by expert clinicians to quality check accurate annotation via the algorithm.

Statistical analysis

Case duration was defined as the time from start of first phase (excluding Preparation) to end of last phase (excluding Wound Closure). Each phase duration was defined as the time from start of the phase to start of the next phase.

A comparison of overall duration of surgery as well as duration of each surgical phase was performed between the groups: junior trainees vs. consultants, junior trainees vs. advanced trainees, advanced trainees vs. consultants. All distributions were non-normal, therefore, non-parametric Mann-Whitney U-test (when variances were approximately equal) or a Brunner-Munzel test (when variances not equal) were used to compare case and phase durations.

Competent and proficient efficiency benchmarks were determined using median case and phase duration values for advanced trainee and consultant cases respectively.

<u>Phase II</u>

Having trained and demonstrated AI validity on recorded cataract surgery in Phase I, this phase moved onto its feasibility through live deployment in the operating room (OR). The system (illustrated in *Figure 1*) captured the surgical view from the microscope and fed this live feed to the AI through a wireless encrypted router. The AI then undertook its real-time analytics and displayed the live results on the screens deployed in the theatre.

These auxiliary screens illustrated the phase of the operation and displayed the phase time, visible for all the wider team to see. The operating surgeon screen displayed the current surgical phase and associated risks. The surgical assistant screen displayed the current surgical phase in real-time, a reference image, and associated steps within that phase. The scrub nurse screen displayed the instruments required for the current and upcoming surgical phase of the procedure as well as tips.

The hardware to support these screens (DS1 Computer) was portable and easily connected to the microscope (*Figure 1).*

Pre- and post-operative metrics were recorded, including patient information, such as cataract type, age and gender, surgeon grade, complications, and their predicted and actual post-op refractive index.

Efficiency metric comparisons were analysed following propensity score weighting(9) to adjust for patient factors and surgeon experience. A patient's propensity score is the predicted probability of them receiving a given treatment given their confounding factors e.g. age, gender.

In this analysis, propensity score weighting was used to adjust for surgeon experience, patient age, gender and cataract type (Cortical, Nuclear or Other).

Results

As part of the AI algorithm training, a total of 923 videos were uploaded from MEH to the TSE video platform.

<u>Phase I</u>

217 patients were recruited and their cataract surgery video recorded. 25 videos were excluded from analysis as the complete case was not captured, leaving 192 cases for analysis. 68 cases were by consultants, 59 by advanced trainees and 65 by junior trainees. The average case duration for consultants (proficient benchmark), advanced trainees (competent benchmark) and junior trainees was 11.3, 17.9 and 21.6 minutes, respectively (*Figure 2*). There was a statistically significant difference in all three inter-group comparisons as follows: consultants vs advanced trainees: 1.3x10^-10, consultants vs junior trainees: 0.0,

advanced trainees vs junior trainees: 5.4x10^-4 (*Figure 3*). There was also significantly more variation in case duration for junior trainees compared to more experienced groups ($p<0.01$). Consultants spent less time on all phases when compared to advanced trainees except for the Application of Viscoelastic phase, usually performed prior to Capsulorhexis and Wound Closure, where no significant difference was found *(Figure 3)*. Consultants spent significantly less time on all phases than junior trainees. Advanced trainees performed the Main Port Incision (0.3 mins faster $p<0.01$), Capsulorhexis (0.7 mins faster $p<0.01$), Intraocular Lens Insertion (0.2 mins faster $p<0.01$) significantly faster than junior trainees. There was no difference in time taken to perform the other phases with the exception of Viscous Agent Removal, which was performed slower by advanced trainees compared to junior trainees.

Mean inter-surgeon variability in phase duration was 37%, expressed as a percentage of mean phase duration. Junior trainees exhibited more variability than advanced trainees and consultants across phases, with some exceptions *(Table 1)*. *Figure 3* shows the phase analysis for all phases. Capsulorhexis demonstrated the largest duration difference between the group medians with median phase durations of 1.1 (n=68), 1.3 (n=59) and 2.0 (n=65) minutes for consultant, advanced and junior trainees respectively.

Deriving Efficiency Benchmarks – Individual Surgical Phases

		Experience of Surgeon		
		Junior Trainee	*Advanced Trainee*	*Consultant*
Phase of surgery	*Paracentesis*	*20.1 %*	*12.7 %*	*25.6 %*
	Application of Viscoelastic	*60.7 %*	*37.8 %*	*59.0 %*
	Capsulorhexis	*42.3 %*	*37.5 %*	*16.4 %*

	Phacoemulsification	*50.9 %*	*29.2 %*	*29.1 %*
	Hydrodissection and Lens Mobilization	*60.6 %*	*17.5 %*	*0.0 %*
	Irrigation and Aspiration	*33.2 %*	*17.5 %*	*30.5 %*
	Re-viscoelastication	*0.0 %*	*0.0 %*	*16.4 %*
	Intraocular Lens Insertion	*0.0 %*	*0.0 %*	*16.4 %*
	Viscous Agent Removal	*16.9 %*	*17.5 %*	*37.3 %*

Table 1: Variability of the duration of each phase within each group of surgeon, stratified by expertise, expressed as the standard deviation of phase duration divided by the mean phase duration.

Phase II

140 cases by 15 surgeons were included in the real-time AI study. 40 were excluded due to the recording being incomplete or due to missing patient information. Efficiency metrics for 76 cases performed with auxiliary screens available in the OR, displaying phase relevant information powered by AI, were compared to 26 without. Inclusion and exclusion criteria are listed in *Patient Recruitment*.

Using propensity score weighting to control for confounding patient variables, there were significant differences in some phase durations with and without the real-time auxiliary screens; Viscoelastic Application, Capsulorhexis, Hydrodissection and Lens Mobilisation. When using real-time ML, the Capsulorhexis, Hydrodissection and Lens mobilization phases were significantly shorter ($p<0.01$ and $p=0.01$ respectively). The use of real-time ML was found to reduce the duration of Capsulorhexis by 30 seconds on average (22%). This phase was found to be the one with the largest difference between the junior and advanced trainees, shown in *Figure 3*.

We also found (with propensity score weighting applied) that cases performed by a consultant and using the auxiliary screens were significantly shorter compared to those without (12.0 mins compared to 14.9 mins, p=0.015 (see *Figure 4*)). The same is true for junior trainees, however, in this case there were not enough cases without screens to determine significance.

Discussion

With this study, we validated and applied an AI system in a real-world setting. In doing so, we demonstrate the first use of AI systems (including real-time AI) for the purpose of increasing operative efficiency in cataract surgery.

AI-drive surgical workflow detection

We developed and assessed a new AI tool applied to cataract surgery. This evaluated previously validated metrics (including time taken), for previously reported cataract phases, in 3 previously defined grades of surgical experience (junior trainee, advanced trainee and consultant surgeons). The comparison of a new tool with previously validated and reported data was important to establish the accuracy of the AI. The AI can also report on whether there was a change in the order of some surgical phases (potentially defining complications or deviation). Whilst seemingly simple, this has very significant potential implications. The AI can help with defining individual surgeons' normal timings, phase flow and hence define any deviation, alerting the team to this, as it may highlight a potential problem or difficulty during the case.

A future development of the tool could provide insights into each surgeon's preference, in relation to bespoke workflows or the pre-populated instrument information provided to the scrub team in the OR. It could inform all members of the team what instrument the surgeon is likely to need next and when, if there is a deviation what they may need and therefore help with a number of efficiency and safety domains, all in real-time.

Quantifying surgical workflows through the use of AI-driven phase segmentation could also help target specific areas of training not limited to surgical training. Team training for all can be applied here including new/temporary members of staff or staff rotation during a list on the day with a seamless guide to help them. It can also inform the management of lists with more accurate data on the surgery. It will be telling to evaluate data not captured by the AI (including the non-operative and change over time).

Real-time AI in practise

We deployed the real-time AI auxiliary screen system in theatre at MEH (*Figure 1)*. This demonstrated the ability of the system to perform real-time intra-operative phase detection in the real-world cataract surgery setting, as well as its potential to increase efficiency. The phase detection AI was also tested on videos obtained from many London MEH sites serving one of the most ethnically diverse populations in the world, with a huge range of cataract types.

With this system in action, there was a significant decrease in case duration for consultant surgeons. Also, for all surgeon grades, significantly less time was spent on a key surgical phase, Capsulorhexis.

This is the first time an AI system has been successfully piloted in a live OR setting for assessing efficiency metrics in cataract surgery. The addition of extra displays with all the additional data served to highlight the information, not currently available, to the wider team.

Why did real-time AI improve efficiency?

There are many explanations as to why real-time feedback may increase efficiency. The most common themes expressed by our participants included increased extended surgical team engagement and surgical awareness. With each surgical phase displayed in real-time on a tailored screen, the surgical scrub team felt more engaged and able to adapt to the specific needs of the surgeon. For example, phase instrument display can be tailored to a specific surgeon, preventing the opening and use of unnecessary instruments. The scrub team not relying on the microscope video feed to self-identify the surgical phase also allowed a reduction in the 'handover time' of surgical instruments to the surgeon when needed. Essentially, this minimises downtime, thereby increasing efficiency.

Increased surgical awareness was provided through the displayed data on phase duration in real-time, promoting regular reminders in relation to maximising efficiency of intra-operative time. Whilst the aim is to improve efficiency, it is important not to overlook the importance of surgical concentration by minimising distractions and reducing stress for the surgeon, assistant, and patient.

Outside of ophthalmology, in general surgery, AI has shown to significantly improve complication prediction accuracy by 25%, reduce intraoperative errors by 18%, and reduce surgical time for complex cases [14].

Potential of real-time AI in cataract surgery

The surgical workflow detection this real-time AI system demonstrates has vast potential for application in a 'smart' theatre of the future.

Through pattern recognition and phase detection in real time, surgical monitoring by less experienced teams should become possible. This should have implications in improving the quality of surgical assistance, particularly in multidisciplinary teams. In the future, a fully automated system could learn to 'send' for the next patient on the operating list when optimal, allowing a reduction in down time in cataract theatre, freeing up OR staff for other tasks and increased throughput. The data generated could also be used for auditing purposes and quality improvement as part of Clinical Governance.

Comparison with previous work

There are several examples of previous work applying computer vision to analysis of cataract surgery. Our own group has previously utilised motion tracking in order to measure characteristics of surgical manoeuvres and how they vary with surgical experience and phase of surgery [10]. The present approach has a number of advantages, namely, TSE AI has been trained to interpret images from a range of microscopes using video of variable quality and stability, a larger sample size and analysis of every phase in the operation.

Other AI systems that are able to detect cataract surgical phases have recently been reported [15, 16]. However, our work is the first to apply an AI phase detection system to answer efficiency-related questions, such as the differences in operating time between junior and senior surgeons. The collection of such data has, until now, relied upon manual recording of data, with a small number of cases [17]. Prior studies are also limited by the amount of detail that can be captured in the data; Nderitu et al. describe 9,552 surgical cases retrospectively in terms of just 11 categorical variables as recorded in the clinical notes [18].

Limitations

Real-time AI primarily focuses on efficiency metrics, leaving the quality of task completion - such as capsulorhexis size - unevaluated. Surgeons, aware that their procedures were being recorded, may have prioritised speed over precision.

The adoption of real-time AI will necessitate adjustments to surgical habits, along with implementation costs and team training. While we believe the efficiency gains offered by real-time AI are substantial, conducting a comprehensive cost-benefit analysis was beyond the scope of this study.

Lastly, the novelty of new technology may lead to an initial surge of enthusiasm that could diminish over time. However, AI is now becoming increasingly integrated into surgical practices, suggesting its sustained relevance and growing adoption.

Conclusions

We have demonstrated the research application of a novel AI phase detection and real-time auxiliary screen system designed for use in cataract surgery. The validity of these tools has been demonstrated in addition to their potential to increase surgical efficiency.

The deployment of AI-based phase detection to cataract surgery opens the door to a new era of surgical data analysis and enables clinicians for the first time to perform detailed observational studies in order to answer scientific questions about optimal surgical technique and increase efficiency.

In addition, real-time AI with the use of auxiliary screens also has the potential to reduce surgical inefficiencies and support a fundamentally different and more efficient cataract surgical theatre of the future.

Acknowledgements

This was a collaborative study between Digital Technologies, Medtronic and MEH, funded by Innovate UK Digital Health Technology Catalyst Round 2, part of UK Research and Innovation [105414 : AI-CARE - Artificial Intelligence for CAtaract surgery Risk Estimation and reduction].

Conflict of Interest

Medtronic, provided access to TSE for video recording, annotation, and analysis throughout this study. Auxiliary intra-operative screen design and implementation were provided by Medtronic.

Authors IL, CA, SB, RM, LC, EJ, PH, KK and DS are employees of Digital Technologies, Medtronic. No direct funding was issued from Digital Technologies, Medtronic for this study.

Contributors

Conception and design of the study (GS, JW, KK, DS and DL); data collection (all authors); writing of the manuscript (all authors); preparation of figures (IL, CA, SB, RM, LC, EJ, PH, KK); supervision (GS); review and discussion of the results (all authors); edition and revision of the manuscript (all authors). The Moorfields Cataract AI Study Group (Collaborators) were involved in recruitment and data collection. GS is the guarantor.

Ethics Statement

Patient consent for publication

Consent obtained from patients.

Ethics approval

This study involves human participants and full IRB and ethics approval were awarded for this study (REC: 14/WM/0038) from the West Midlands - Coventry & Warwickshire Research Ethics Committee. Participants gave informed consent to participate in the study before taking part.

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Figure Captions

Figure 1: Three intra-operative screen displays, a photo of the screens in-situ in the operating theatre, DS1 computer and controller. Note that the microscope connects to the DS1 Computer via a video cable. Intra- operative screens are powered by the real-time AI phase detection algorithm. DS1 computer and controller (the two hardware components of TSE) are connected via wireless internet provider.

Figure 2: Case durations for consultant, advanced trainee and junior trainees with median case durations 11.3 (n=68), 17.9 (n=59) and 21.6 (n=65) minutes respectively and n is the number of complete cases.

Figure 3: Phase duration in minutes for consultant (pink), advanced trainee (blue) and junior trainees (orange).

Figure 4: Weighted case duration split by surgeon experience with (dark blue) and without (light blue) real- time ML

Figure 1: Three intra-operative screen displays, a photo of the screens in-situ in the operating theatre, DS1 computer and controller. Note that the microscope connects to the DS1 Computer via a video cable. Intra-operative screens are powered by the real-time AI phase detection algorithm. DS1 computer and controller (the two hardware components of TSE) are connected via wireless internet provider.

162x179mm (330 x 330 DPI)

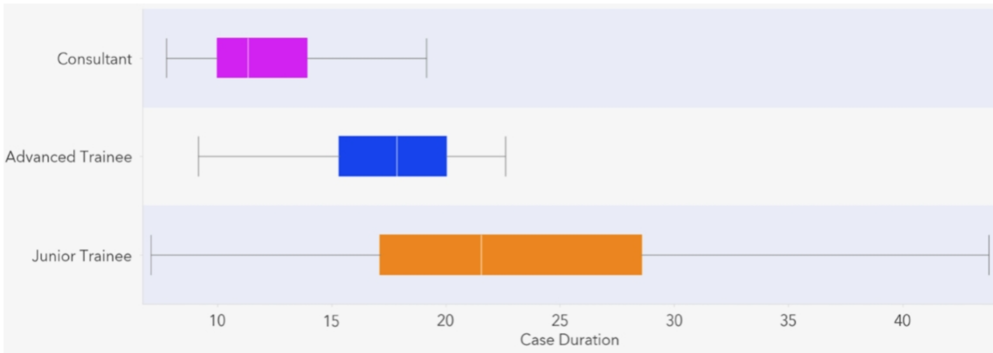

Figure 2: Case durations for consultant, advanced trainee and junior trainees with median case durations 11.3 (n=68), 17.9 (n=59) and 21.6 (n=65) minutes respectively and n is the number of complete cases.

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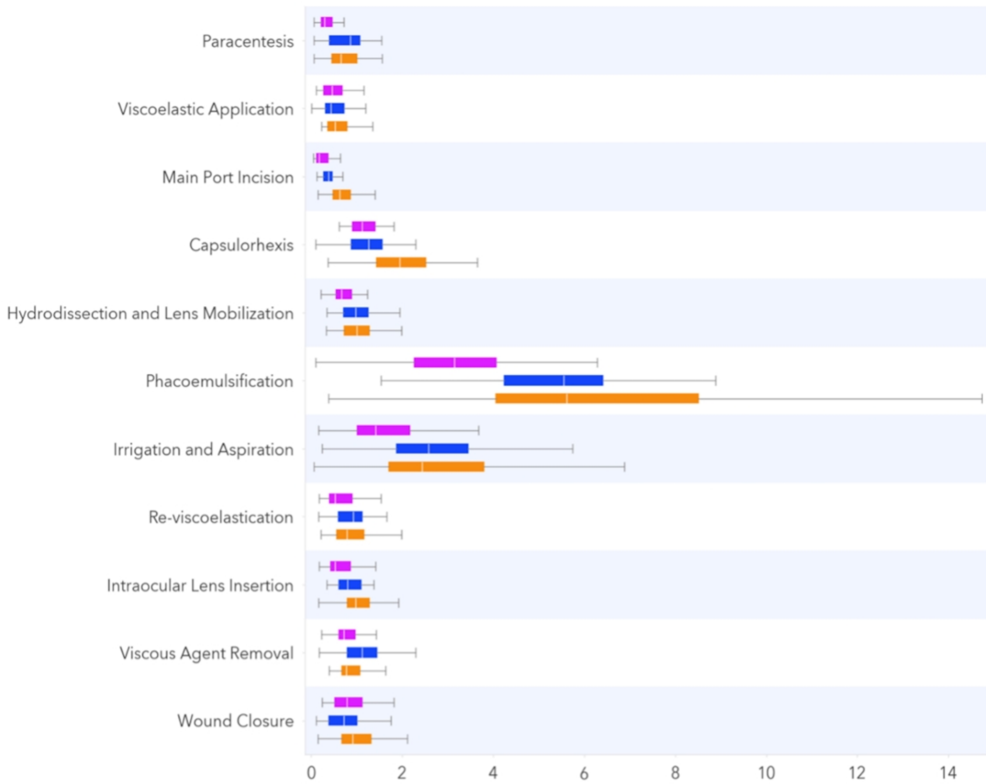

Figure 3: Phase duration in minutes for consultant (pink), advanced trainee (blue) and junior trainees (orange).

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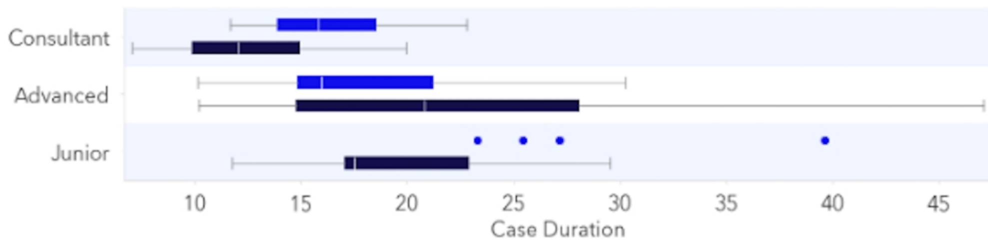

Figure 4: Weighted case duration split by surgeon experience with (dark blue) and without (light blue) real-time ML

152x38mm (1000 x 1000 DPI)

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Elizabeth Nkumba
Emma Gregg
Ernestina Osei
Esther Addae
Eugene Igwe
Eulalia Sotaridona
Feyitimileain Onafowokan
George Voyatzis
Georgios Aspridis
Golda Joseph
Hari Jayaram

Helga Onodi
Ioannis Athanasiadis
Iwona Czyz
Jaheed Khan
James Tee
Jennifer Valentine
Joanne Harris
Joshua Bloore
Joy Gedai
Joyce Amamor
Jutice Brobbey
Kamran Saha
Kate Balagtey
Khadijah Basheer
Kirithika Muthusamy
Krisztina Emeriewen
Layla Juma
Lea Babista
Leira NOVO
Leo Ticao
Lily Aquino
Luccia Murillo
Lucy Ako-Nneng
Lucy Barker
Luke Nicholson
Lyandra Pite
Manisha Gaware
Maria Chuacuco
Marie Rennie
Marina Iaverpino
Melchizedek Penacerrada
Merlyn Sangalang
Mina Ghimire
Moira Harris
Monica Hastabi
Msureen Campbell
Musa Sanyang
Nazmiye Gerc
Norma Machaikata
Norman Ventura
Oksana Wilkinson
Olanrewaju Banjoko
Pablo Acosta
Panagiota Founti
Pei-Fen Lin
Rachel Lorusso
Rajam Azariah
Rajesh Deshmukh
Ramani Aruldhan
Ranjana Timsina

Rashid Mohammed
Ravinder Kaur
Reej Daniel
Remija C. Mpomzi
Renee Yuan
Retno Wulandari
Retno Wulandari
Richard Brookner
Riffat Iqbal
Riffat Iqbal
Roberta Jeffers
Robin Ifi
Romil Patel
Ronald Kam
Roseline Orji
Roxanne Crosby-Nwaobi
Ruby Fronda
Ruel Villaflores
Ruth Guevara
Saab Bhermi
Sana Hamid
Sandra Turner
Sanju Napel
Sharmila Tekriwal
Sharmila Tekriwal
Sharmina Khan
Sharon Heng
Sharon Price
Shashikala Rathod
Shini Johny
Silvana Georgieva
Simone Nepa
Su-yin Koay
Susanna Lui
Susanna Lui
Usha Gurung
Vincenzo Maurino
Violeta Filipova
Vivien Quan
Winifred Kmara
Zubin Saihan