Lanes, Clusters, Lines of Sight: Modelling diagnostic eyecare clinics to improve patient flow

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Abstract

Lengthy waiting times for ophthalmology appointments in the UK National Health Service (NHS) increased further in the immediate aftermath of the Covid-19 pandemic, necessitating a different approach to triaging patients safely and at speed. Moorfields Eye Hospital NHS Trust therefore opened an additional diagnostic hub designed with a linear spatial layout and patient flow system, which is analyzed in this paper in comparison to an existing clinic. We integrate direct observations of patient flows, and an architectural layout analysis based on space syntax methods with queuing simulations from operations research and show that the two clinics operate differently and that both clinics have their advantages and disadvantages. The newly opened clinic with a lane system supports flows and coordination by line of sight between stations, which contrasts with a lack of sightlines in the existing clinic. The latter layout with clusters of stations compensates by enabling a more organic flow especially in conjunction with experienced technicians, which is beneficial when the clinic gets busy. When high patient load is simulated in the queuing models, the lane system results in slightly bigger bottlenecks and longer clinic durations. An ideal allocation of the number of stations to diagnostic activities based on clusters is suggested. This work stands in the tradition of combining architectural and operations research. By reflecting on the variability of diagnostic processes found in our observations, we contribute to the understanding of routines as performative. We also add insight to the growing field of evidence-based design, particularly by highlighting the importance of line-of-sight relationships in ophthalmology.

Introduction

In the UK, waiting times to access the National Health Service (NHS) have risen significantly over the last decade. Ophthalmology, as largest specialty for outpatient appointments in the NHS, with over 8 million attended appointments annually (NHS, 2023), is severely affected. Even before the Covid-19 pandemic, delays were significant, with 3,384 ophthalmology patients in 2017 waiting for longer than a year and 1% of these delayed patients suffering preventable loss of eyesight (Foot & MacEwen, 2017). The Covid-19 pandemic exacerbated these problems, partially due to the suspension of services in early 2020 and partially due to patients not attending scheduled appointments for fear of contracting Covid. Moorfields Eye Hospital NHS Trust in London, for example, was able to see only half of its usual patient numbers in the period of 2020-2021 (from more than 640,000 previously to 340,180) (Moorfields_Eye_Hospital_NHS_Foundation_Trust, 2021).

To support the recovery of services and to accelerate the examination of patients to address the patient backlog, the Hospital opened a new diagnostic center in February 2021, the Hoxton Hub, an additional technician-led clinic that offered diagnostic and monitoring services to patients with glaucoma and retinal diseases. This builds on processes put in place in 2014, when Moorfields opened a so called ‘virtual clinic’ for glaucoma patients which was led by technicians rather than by doctors (Kotecha, Bonstein, et al., 2015), resulting in more streamlined clinical testing, where results were reviewed by clinicians asynchronously and patients that required further care could be triaged more quickly and effectively.

The new Hoxton Hub was set up with a spatially enforced test sequence, as outlined by Kotecha, Baldwin, et al. (2015), differing from traditional outpatient clinics. However, with three parallel lanes aimed at leading glaucoma patients through the required tests one by one, this aimed for efficiencies through clearly structured patient flow. In contrast, another technician-led clinic was configured spatially in a clustered way with stations for tests arranged next to one another inside a larger open-plan space with less obvious patient flow routes. While offering a clear spatial strategy, the linear arrangement of test stations in lanes raises questions of operational effectiveness. Because different clinical testing activities take differing amounts of time, the inflexibility of the lane structure could result in bottlenecks.

Therefore, in this paper we combine clinical expertise in ophthalmology with architectural scholarship on spatial layouts and operational research perspectives to understand patient flows and effectiveness of these two different clinic setups. We use direct observations of the duration of medical tests for patients to establish a baseline data set of current practices; spatial analysis methods building on the theory and method of space syntax (Hillier & Hanson, 1984) to understand consequences of the layout choices; and queuing simulations based on the observed durations of diagnostic activities to identify bottlenecks and model how effective the current setups are, as well as how they might be improved.

The next three sections provide an overview of relevant literature to contextualize our study.

The spatial layout of diagnostic centers

In their seminal book 'The Social Logic of Space', Hillier and Hanson (1984) make the case that spatial structures are not merely the backdrop of behavior but in themselves constitute behaviors, as it is impossible to disentangle human behaviors from the spatial environment in which they unfold. In this sense, space syntax, the theory and method Hillier and Hanson have pioneered "allows us to think of space as already social" (Peponis, 2024, p. 134) and to analyze how spatial configurations structure everyday life.

Space syntax considers space in the form of a network structure, investigating elements (rooms, corridors, staircases) and their connections (doorways) by means of graph theory, providing quantitative measures of how integrated or segregated a location is in the overall spatial configuration, how people can move from one location to another, or how they perceive space from any particular location, and what this means for the potential of a space to be filled with human life. Research across building types has repeatedly shown that integrated spaces with shorter paths to all other spaces in a network are livelier and more populated (Hillier et al., 1996; Hillier & Penn, 1991; Peponis, Zimring, & Choi, 1990). Spatial configuration in this sense has also been called an opportunity structure (Sailer & Li, 2022).

Space syntax has been applied to both urban and architectural scale, and on the building level to healthcare contexts (Zook & Sailer, 2022). Most research in this vein, however, has been on hospitals as a whole (Haq, 2003; Haq & Luo, 2012; Peponis & Zimring, 1996; Peponis et al., 1990) or on inpatient wards (Lu & Zimring, 2011; Ossmann, Bafna, Zimring, & Murphy, 2019; Pachilova, 2020; Pachilova & Sailer, 2020; Rashid, 2015). There is a plethora of research on the layout of hospital wards with less or no space syntax focus but instead including time and motion studies of staff such as nurses (Hendrich, Chow, Skierczynski, & Lu, 2008; Hendrich et al., 2009; Thompson & Goldin, 1975).

In contrast to wards or hospitals as a whole, a focus on the spatial structure of outpatient clinics or diagnostic centers has been rather rare, although noteworthy exceptions exist, for example an investigation of spatial hierarchies of outpatient departments in four geriatric hospitals in Korea including implications for cognition and wayfinding of the elderly population (Lee, Seo, & Kim, 2015); or the comparison of work patterns of physicians, nurses and clerks in outpatient clinics in a hospital in Canada versus one in the Netherlands in relation to their spatial configuration (Pachilova & Sailer, 2013; Sailer et al., 2013). A further paper argued that more open-plan layouts of outpatient clinics resulted in more dynamic work patterns (Sailer, 2024). None of the above cited papers on outpatient clinic layouts investigated patient flows in detail.

Yet patient flows were the focus of a comparative study of spatial layouts beyond the space syntax paradigm; it investigated two different architectural design alternatives for an ophthalmology clinic using agent-based modelling (Schaumann, Putievsky Pilosof, Sopher, Yahav, & Kalay, 2019). The main difference between the two designs was whether waiting areas were centralized or decentralized. Various key performance indicators (KPI) including nurses travel distances, length of stay for patients and patient throughput were simulated, and it was found that the decentralized design improved all three of the above mentioned KPIs, however potentially created physical bottlenecks in particular locations and performed worse on other KPIs. Detailed layout choices were not modelled.

In summary, studies of the spatial layout of diagnostic centers are rare, although studies on wider healthcare settings provide additional context.

Patient flow and operational effectiveness

Operational research methods have had wide application in healthcare (Utley, Crowe, & Pagel, 2022) including the use of queuing analysis (Lakshmi & Sivakumar, 2013), optimization (Crown et al., 2017) and micro-simulation (Brailsford, Harper, Patel, & Pitt, 2009).

Micro-simulation is particularly well suited to modelling the operation of outpatient clinics (Philip, Prasannavenkatesan, & Mustafee, 2023). In the context of a post-term pregnancy outpatient clinic, Viana et al. (2020) used a simulation model of a multi-process pathway to identify bottlenecks and find improved allocations of resource that would increase the effective capacity of the clinic in terms of the number of patients it could cater to.

In the context of ophthalmology, Pan et al. (2015) built a discrete event simulation (DES) model of an ophthalmology outpatient clinic in Singapore and used it to design and conduct in-silico experiments that demonstrated the benefits of changing the appointment system and the potential benefits of moving to dilation-free retinal imaging. Lin et al. (2017) used DES to improve the performance of an ophthalmology clinic catering for multiple classes of patients, with each class of patient describing a particular pathway through a set of multiple activities. By changing resource allocation across the different activities, they were able to reduce a (weighted) sum of congestion, patient waiting time and staff overtime by 43%. Further improvements were available through jointly addressing resource allocation and appointment scheduling and by introducing some on-the-day flexibility in which staff performed which tasks.

To summarize, micro-simulation methods have often been found useful in analyzing and identifying potential improvements to designs of ostensive processes, i.e., their schematic and abstract principle (Feldman & Pentland, 2003).

Combining spatial layouts and operational simulations

A small number of studies have considered both spatial and operational aspects of healthcare settings.

Morgareidge et al (2014) provide an example of work where DES and Space Syntax analysis were used sequentially to inform and then evaluate the location of an Emergency Department in the masterplan of a hospital and then its detailed spatial layout to highlight both the operational and spatial performance of a new design.

Halawa et al. (2020) reviewed the use of operational research approaches in hospital facility design and concluded that more interdisciplinary work is required to bridge the gap between the considerations typically embedded in operational research models addressing facility layout problems (for instance walking distances) and those considerations that occupy designers (lines of sight, access to natural light, etc.). They also call for work that brings these considerations together within optimization frameworks and suggest that simulation-optimization (see: Wang & Demeulemeester, 2023) is the most promising approach for doing so.

Li et al. (2023) use multi-objective optimization approaches to identify Pareto-optimal candidate layouts for detailed evaluation through agent-based simulation, with the intent that modelling tools act to support the work of architects making layout decisions.

In their review of the literature on layout design in health care, specifically focusing on the use of spatial network analysis and simulation modelling to assess layout design at a hospital level, Jia et al. (2023) found that few authors using simulation or other operational research techniques to identify improvements in patient waiting times or patient flow consider explicitly the spatial layout of services. For those studies that did consider the layout, the authors found that papers did not provide clear representations of service layouts.

This goes to show that bringing spatial and operational analysis tools together is a fruitful approach yet with clear gaps in the extant research, for example in using detailed spatial models and in applying this to diagnostic centers.

Study focus

The aim of this paper is to investigate current practices of eye examination and spatial arrangement at Moorfields Eye Hospital, and to compare and contrast the two different layouts used at the time to gain insights into spatial and operational setups likely to improve the flow of patients in time and space against the background of long NHS waiting lists.

From a spatial analysis point of view, we will use more fine-grained techniques than the axial line models that Morgareidge et al. (2014) utilized. Instead of conceptualizing each corridor as a line of movement and connecting them into a network, we will use models of visibility and isovist analysis that represent human perception more closely and in finer resolution (Sailer, Koutsolampros, & Pachilova, 2021; Wiener et al., 2007), which is useful for the smaller scale environments of diagnostic centers.

We do not present an integrated modelling approach that brings considerations of space syntax into (or under the bonnet of) optimization or process simulation, but rather, similar to Morgareidge et al. (2014) and Li et al. (2023) use space syntax methods, micro-simulation and simple optimization techniques separately in an interdisciplinary study of clinic layouts intended to provide insights for future clinic designs.

Research questions

Building on the above background and extant literature, we are addressing the following research questions in this paper:

1. Which underlying spatial network structures were in use at the two diagnostic centers?
2. How are the two centers operating regarding the length of the diagnostic processes, the numbers of patients being seen and accumulating waiting times?
3. Which implications do spatial network structures have on flow processes?
4. Can the test stations be arranged differently to ease the diagnostic process?

Methods and data

Study context

This study compares the spaces offered to glaucoma patients in two different clinics, which are part of the Moorfields Eye Hospital NHS Trust in London. The first, the Cayton Street clinic, a converted space on the main hospital campus, features a more traditional clinic layout with a reception, a waiting space, two larger, open-plan exam rooms, and several smaller, enclosed exam rooms. The second clinic, the Hoxton Hub, which opened in 2021, a few months prior to the study to provide an additional diagnostic space for patients, offers a reception space and, in the majority, is structured as a system of parallel lanes, separated by high partitions (see figure 1 for floor plans of both clinics). More enclosed rooms are situated alongside the lanes, mainly used for another clinical pathway (medical retina). It was deliberately constructed to ease patient flow. The comparison of the two different settings affords an opportunity to understand the impact of layout choices on patient flow and thus to investigate operational efficiencies in comparison.

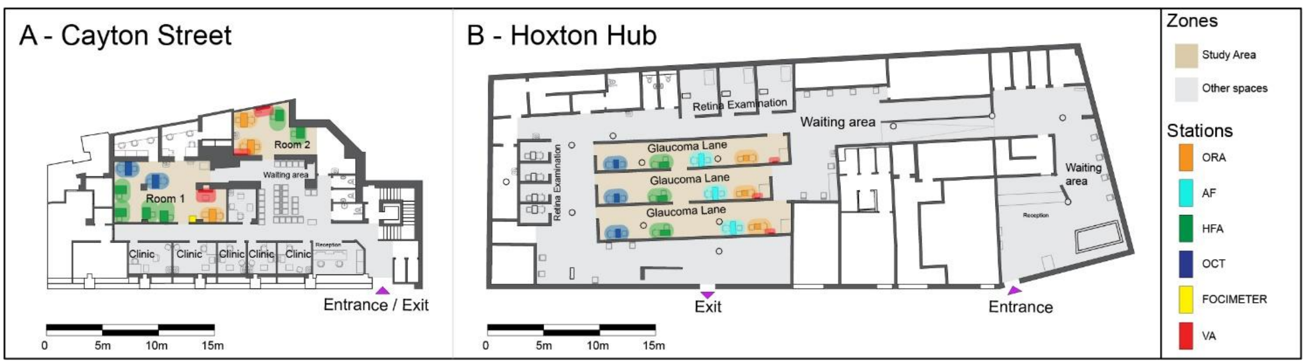

Fig 1. Annotated floor plans of the two clinic layouts. Corridors and exam rooms unrelated to the study are shown in grey. The focus area of the study is colored in light brown. The five different types of stations are highlighted by colored dots (orange: ORA, cyan: autorefractor, green: HFA, blue: OCT, yellow: focimeter, red: visual acuity).

A standard patient examination process for the glaucoma pathway consisted of a series of five diagnostic activities, also referred to as stations in the following, as each piece of examination equipment was provided at a different table and patients moved from one station to another in their journey through the clinic.

Those were: 1) a test of visual acuity (VA) using a chart on the wall; 2) a measurement of a patient's refractive error, hence the prescription for glasses (where applicable) using a focimeter in Cayton Street and an autorefractor (AF) at Hoxton; 3) eye pressure and corneal biomechanics on an Ocular Response Analyzer (ORA); 4) a visual field test on a Humphrey Field Analyzer (HFA); and 5) retinal imaging on an Optical Coherence

Tomography (OCT) machine. The typical duration of each examination varies where stations such as VA, AF and ORA would be expected to be shorter while HFA and OCT were expected to take longer.

Glaucoma patients in Cayton Street were seen in two open-plan exam rooms linked by a corridor. A central waiting area was located alongside the connecting corridor. Room 1 contained one VA, one ORA, one focimeter, two OCTs and four HFAs. Room 2 contained two VA, two ORAs and two HFAs.

In the original layout of the Cayton Street clinic, designed and established in 2017, the glaucoma pathway only used the larger of the two rooms (Room 1), thereby maintaining direct line-of-sight among all technicians. However, due to the Covid-19 distancing regulations in place at the time of the study in the summer of 2021, both Rooms 1 and 2 were used in parallel for the glaucoma clinic.

The glaucoma pathway at the Hoxton Hub was comprised of three lanes with a waiting area at the beginning of the lanes and another waiting area at the end of the lane. Each lane contained one station per exam type (VA, ORA, AF, HFA, OCT) and the stations were positioned in the same order in each lane. The wall partitions were high so there was no visibility between lanes except for a wall opening in the middle of each lane which allowed staff and patients to cross from one lane to another if needed.

The spatial location of all stations is highlighted in figure 1 as well.

Ethics

The study was classed as a service evaluation and was therefore exempt from NHS ethics approval. The study protocols (see supplemental material S1) were approved by the board of the Moorfields NHS Trust. A full risk assessment was undertaken and approved by the university. No personalized data was collected; all staff members were informed prior to the study and gave their consent orally. Patients were informed of the presence of service evaluation observers upon arrival at reception.

Data collection and sample

Fieldwork was undertaken in June and July 2021. Two main data sets were collected: 1) an up-to-date floor plan of each clinic including the locations and types of all diagnostic equipment marked up, and 2) direct observations of glaucoma patient flows, recorded on tablets, including exact time stamps of entry and exit of the clinic as well as start and end times for all diagnostic tests.

At reception, patients received a sticker with a study ID number, which was recorded by observers as an identifier. Over the course of ten days of observations, the observers captured nine 4-hour shifts in the period from 8:30 to 17:00 in Hoxton and six 4-hour day shifts and seven 3-hour evening shifts between 8:30 and 20:00 in Cayton Street. 14 patients at Cayton Street and 11 patients at Hoxton were shadowed for the entirety of their journey through the clinics with an average duration of 36 minutes (range 19-70min) and 37 minutes (range 26-79min) respectively. The majority of the data, however, was captured by additional, so called 'zonal' observations, where each observer was placed in a position to monitor a discrete space as well as all start and end times of diagnostic tests completed in this area, resulting in a total of 152 and 83 unique patients observed in the clinics respectively. From these data, full patient journeys were reconstructed using the patient identifiers. Aggregating data from both observation methods resulted in a sample size of 621 single data points of activity durations in Cayton Street and 485 at Hoxton (which includes observed activities of standing and waiting), hence n=1106. This full data set contained a subsample of actual examinations at stations (excluding standing and waiting) of n=1007.

Patient and technician data

Each observer was asked to record an identifier for each technician looking after a patient, i.e., the first two letters of the technician's first name and the first two letters of their last name. Each technician was wearing a name tag which was visible to the observers. This was used in the analysis stage to understand technician workflows, for example whether they guide a single patient through every stage of the diagnostic process, or whether they mainly stick to a particular diagnostic activity. Afterwards all identifiers were anonymized.

The observers were also asked to assess and record the fluency in English of each patient where they could choose from four levels: 'fluent', 'few issues', 'many issues', and 'translator'. Using the patient ID numbers, which were cross-referenced by hospital staff to their patient database, additional information was obtained from the hospital including age, gender, and if the patient was a first time or a follow-up patient.

The observers also recorded anything they felt worth noting down in the form of a qualitative note. This included reasons for occurring delays, causes for waiting, patients with mobility difficulties, etc.

In summary, for each diagnostic activity, the following data was collected: 1) patient ID, 2) date, 2) exact time stamps for the moment a patient sat down at each station (start time), and got up again (end time), 3) location (corridor, waiting area or station number), 4) activity (exam, wait while sitting, wait while standing), 5) technician ID, 6) English proficiency, 7) qualitative notes (see supplemental material S1 on the observation protocol).

Space syntax metrics

Two types of spatial analysis were used to study and compare the layouts of the two clinics. These were:

1. A *Justified graph (j-graph),* which is a visualization and analysis method whereby a particular space is selected as the 'root' and the other spaces in the graph are then aligned above it in levels according to how many spaces one must pass through to arrive at each space from the root. In the traditional j-graph analysis (Hillier & Hanson, 1984), a spatial element is defined by means of a convex breakdown (i.e., the whole space is divided into discrete chunks starting with the fattest and satisfying convexity so that any point within a space can see all other points directly); then each convex space is represented as a node and organized visually starting from the root and then all spaces with depth 1 from the root are aligned immediately above it, all spaces at depth 2 from the root above those at depth 1 and so one until all levels of depth from the root are accounted for. In the context of this paper, the root is the clinic's entrance, and the spatial elements of interest are the individual stations and the corridors leading from the entrance to the stations and then to the exit point. The lines that link the nodes represent the connections between the elements of interest in the graph. Hence, we deviate from convexity by not considering the fattest spaces but rather functional spaces of interest, and by considering not the transition from one space to another as links but the transition of patients from one diagnostic activity to another, as manifested in the best practices in place, which were also used to determine the order of stations in the Hoxton Hub layout. This represents ostensive routines. Yet, we still build on the advantages of the method in highlighting the spatial relations very clearly.
2. A *Visibility Graph Analysis (VGA),* which is a method of analyzing the intervisibility between different spaces in a building based on isovists (Benedikt, 1979). An isovist represents all visible areas on the floor plan around a generating point in 360 degrees. A visibility graph imposes a grid spacing of 0.6 by 0.6m on top of a floor plan (roughly the size a human occupies in space), then constructs an isovist from the center of each pixel of the grid and connects every pixel to those pixels that fall within the isovist area. Thus, the pixels serve as vertices and the visibility relationships between pixels as edges resulting in a visibility graph of locations within space (Turner, Doxa, O'Sullivan, & Penn, 2001). Depthmap X software

(depthmapX_development_team, 2020) was used to generate and analyze the visibility graphs. A VGA was constructed on eye-level based on the assumption of seeing as an important mode of perceiving buildings (Hanson, 1998). How integrated or segregated a space is within a building is visualized by using a red to blue color heatmap scheme where highly integrated areas are shown as warm and highly segregated areas as cool colors. Thus, the visibility graphs can be analyzed visually as well as statistically through measures of graph centrality.

We rely on the following metrics derived from the above:

1. *Step Depth (SD)* is a metric which is used to illustrate how deep (how many steps removed) a particular location is in relation to another location. It can be applied to a j-graph, but we mainly use it in the context of the VGA to illustrate the shortest visual distance between two points of interest, or how many visual steps it takes (equivalent to 'looking around the corner') to gain awareness of one station when positioned at another.
2. *Mean depth (MD)* builds on step depth conceptually, and applied to a VGA is defined as the mean number of visual steps required from any generating isovist location to reach all other locations in the spatial network. Thus, it is conceptually similar to closeness centrality as defined in graph theory. Mean MD then describes all MD values of all isovist generating locations averaged across a whole spatial network.

Queuing simulation

For the queuing simulations, we first identified the ostensive processes as a baseline for comparison. This included the set of five diagnostic activities that patients attending the glaucoma clinic complete, in the preferred order as specified by the consultant ophthalmologists on the research team (and which follows the Hoxton Hub layout). To characterize the process-design of an observed or hypothetical clinic, we constructed a diagram specifying the distinct path(s) permitted for patients to take through a set of stations, with each station devoted to a particular diagnostic activity.

Secondly, to simulate the clinic, we built a micro-simulation model to directly compare the anticipated performance of different clinic process-designs in terms of a range of metrics including the time that patients spend waiting, queue sizes, equipment utilization, overall clinic duration and peak number of patients in the clinic.

The simulation model was built using an approach called queue departure computation (Ebert, Wu, Mengersen, & Ruggeri, 2020), which provides a way of studying networks of queues characterized by patient-to-patient variability that gives equivalent results to the computationally less efficient but more flexible and widely used approach of DES.

In this approach, the times at which individual patients arrive at the clinic and the times they take to complete each activity and to move between activities are set according to experimental appointment schedules and sampled from distributions of observed data *prior* to simulating the operation of the clinic.

A single run of the simulation starts by applying an algorithm that determines the time and station at which a patient starts their first activity and calculates the time at which they complete it, using this completion time as the time at which the station they used becomes free for another patient and to calculate (by adding a transit time) the time they arrive at the queue for their next activity, with which queue they visit next taken from the ostensive process-design. The algorithm is used iteratively until the arrival time, the station used, the start time and the end time is calculated for each patient for each activity.

From this set of outputs, performance metrics can be calculated and stored for this single run of the simulation. Further runs of the simulation are performed by first setting and sampling a different set of patient clinic-arrival times, activity times and transit times.

The clinic simulation was implemented in R version 4.2.2 (R_Core_Team, 2022) using the package Queue Computer (Ebert et al., 2020). Our code and input data are available (Sailer et al., 2024).

We use observed data in the simulation experiments as follows. For each of the clinic process-designs considered, we evaluated its anticipated performance in a clinic session catering for 60 patients scheduled to arrive in batches of three. To understand how any differences in anticipated performance between process-designs varied with increasing work-intensity, we conducted six experiments for each design with the interval between batches reduced from 30 minutes to 5 minutes in steps of five minutes.

For each experiment, we ran the simulation 100 times, and the associated appointment schedule determined the clinic-arrival times for the 60 hypothetical patients. A set of five activity times was selected at random (with replacement) from the sets of activity times observed among patients at the Hoxton Hub for each of the 60 hypothetical patients. This sampling was done at patient level to reflect that patients who took longer than average to complete one activity were more likely to take longer than average to complete other activities. Note that, as the focus of these experiments was to generate insight on any differences in performance intrinsic to clinic process-design, we used the Hoxton Hub activity times in all experiments, made simplifying assumptions that all patients would attend and arrive on time and set transit times between activities to a uniform ten seconds.

Activity times for the 60 hypothetical patients differed from run-to-run within an experiment but were identical for corresponding runs in different experiments (across ostensive process-designs and work-intensities).

Finally, summary performance measures for each clinic process-design under each experimental setting were calculated from the output of the 100 multiple runs corresponding to that experiment. Using the same sets of clinic-arrival, activity and transit times gave a direct comparison of the performance attributes of the clinic process-designs considered.

To suggest a balanced allocation of capacity across the different diagnostic activities, we used analytical optimization. Three of the process-designs evaluated using the clinic simulation were taken from discussions with consultant ophthalmologists on the research team and related closely to intended operations at the two clinic sites. In short, they were: 1) lanes of grouped activities (group 1: VA, ORA, AF, group 2: HFA, OCT) with queuing only between groups; 2) lanes of ungrouped activities with queuing at every transfer; 3) banks with three stations per activity with queuing at every transfer. A fourth process-design was obtained by solving the integer linear programming problem shown in figure 2. Detailed diagrams of all four models are presented in the results section (figure 9a-d).

Maximise throughput of T patients per unit time subject to the constraints that

$T\bar{d}_i \le x_i$ for all activities i (1)

$\sum_i c_i x_i \le B$ (2)

$x_i \ge 1$ for all activities i (3)

x_i integer.

Where $\bar{d}_i$ is the mean duration of activity i, x_i is the number of stations dedicated to activity i, c_i the "cost" of deploying each station dedicated to activity i (financial or in terms of space) and B the associated available budget.

Constraints (1) ensure that the average demand for each activity does not exceed the allocated capacity, constraint (2) ensures that the budget is not exceeded, and constraints (3) ensure a clinically viable design that has at least one station dedicated to each activity.

Fig 2. Overview of the analytical optimization approach used to determine what would constitute a balanced allocation of resources across the five different activities if constrained to a maximum total number of stations.

Results

We will discuss results in four consecutive sections corresponding to the four research questions we raised.

The spatial logic of the two clinics

The two sites are significantly different in terms of how the diagnostic activities are arranged spatially.

The Cayton Street clinic (see figures 3a and b) is organized in two clusters of nine and five stations where patients in the smaller cluster (room 2) have to go from the HFA to the bigger cluster to use the OCT stations but other than that, the type and number of stations in each cluster should allow for patients to stay within their room. The two clusters are clearly identified through the j-graph in Figure 3a where the arrangement of the clusters follows the technicians' workflows. The connection from the HFA in room 2 to one of the OCTs in room 1 is via the corridor.

In contrast, the stations in Hoxton (see figures 3c and d) were organized in a linear way from the start so once a patient entered a lane they were meant to go through each station of this lane and exit the lane from the other side. The three lanes are clearly identifiable through the j-graph in Figure 3c where each lane consists of five stations following a specific ostensive sequence.

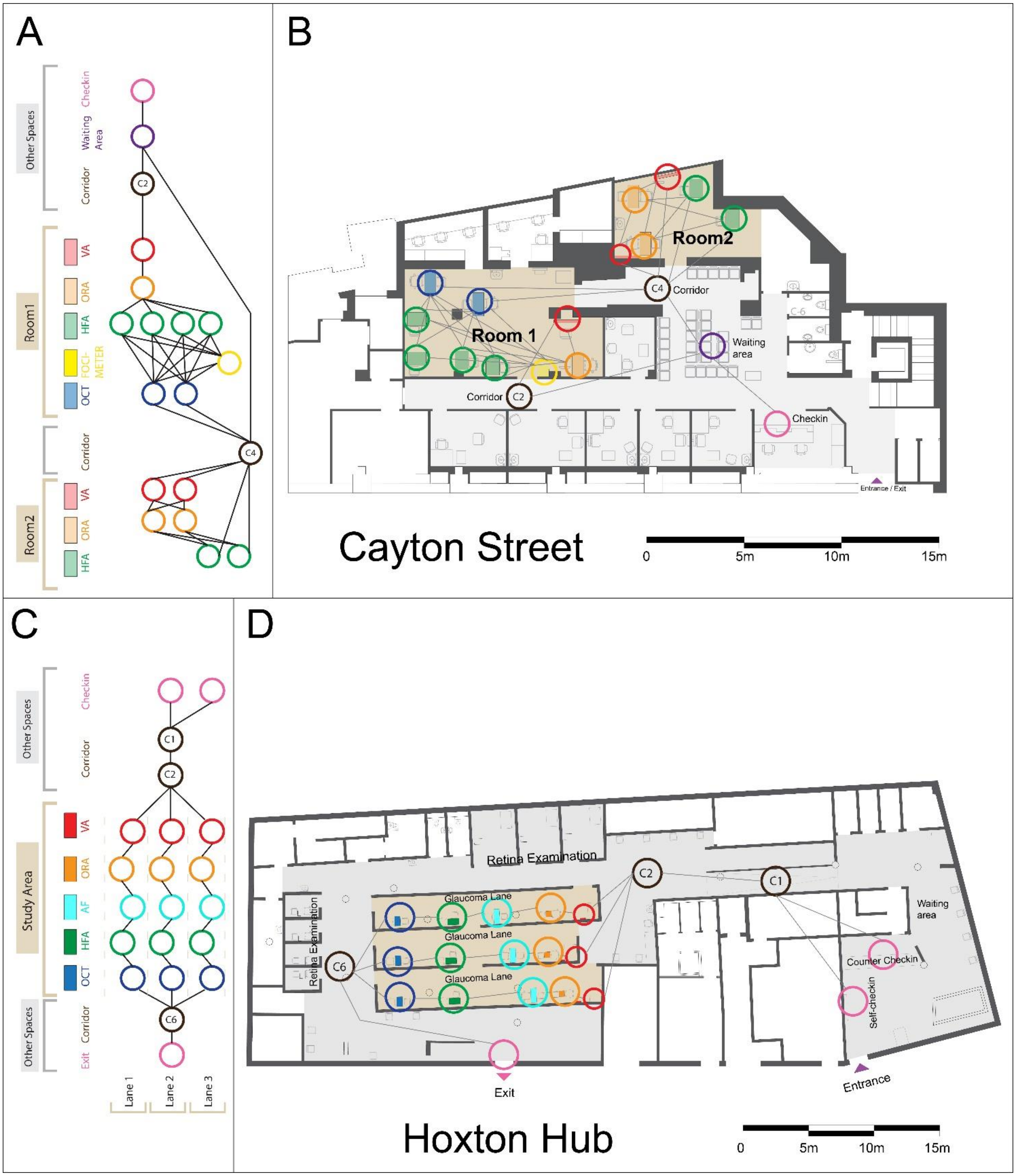

Fig 3. Spatial organization of the two clinics with a j-graph of Cayton Street (a) and its corresponding detailed plan (b), a j-graph of the Hoxton Hub (c) and the detailed plan (d).

The VGA analysis of the clinics (figure 4a-d) shows that the Hoxton Hub is deeper as a whole than Cayton Street, with an average MD of 2.7, so almost three visual steps are needed to reach all spaces from any starting location compared to 2.4 in Cayton Street (see table 1 for details). However, this is mostly a result of the size of the clinic since Hoxton has almost double the area of Cayton Street. The step depth analysis (figure 4c-d) from a sample station (we selected an ORA in both clinics) illustrates that Room 1 in Cayton Street is two visual steps away from Room 2 while in Hoxton all the stations in each lane are fully visible while the neighboring lanes are just one visual step away, which has implications on the workflows and operational performance discussed in the following section.

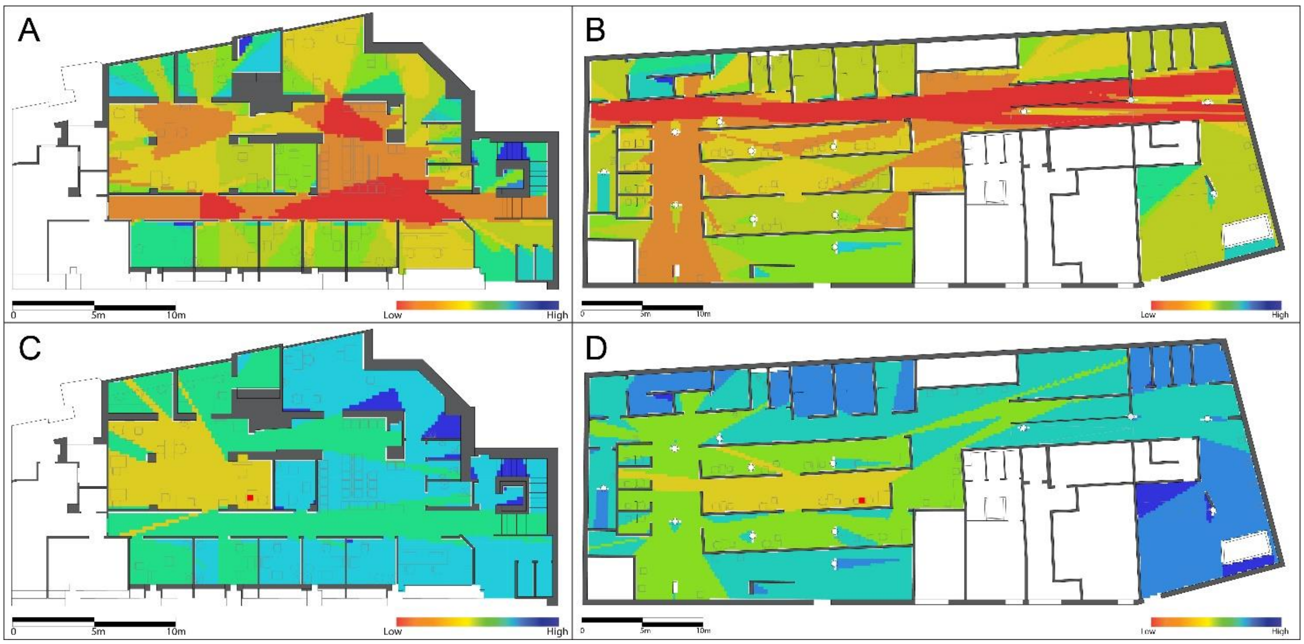

Fig 4. VGA diagrams of the spatial logic of the two clinics, showing mean depth in Cayton Street (a) and the Hoxton Hub (b) as well as step depth from an ORA station (signified by a small red dot) in Cayton Street (c) and the Hoxton Hub (d). Lower depth is shown in warm colors, whereas high depth is shown in cool colors.

Clinic	Min MD	Mean MD	Max MD	St.dev MD
Cayton Street	1.7	2.4	3.7	0.4
Hoxton Hub	1.9	2.7	4.9	0.4

Table 1. Mean Depth statistics showing minimum, mean, maximum MD and standard deviation of Cayton Street and the Hoxton Hub.

Observations of the operational performance of the two clinics

Patient populations visiting the two clinics were broadly comparable. 96% in Cayton Street were fluent in English versus 86% of the patients in the Hoxton Hub. The ratio of male to female patients was 1.3:1 across both clinics. The average age of patients in Cayton Street was 63 with an age range of 25-89 years while in Hoxton the average age was 65 with an age range of 41-95 years.

Direct observations highlighted commonalities and differences in the durations of each diagnostic activity across the two clinics. Due to significant outliers in the duration of the examinations, we report a 95% trimmed range to highlight what is happening on the ground in a typical process. The full range of data in comparison to the 95% trimmed range is shown in supplementary material S3.

Station	**Cayton Street**				**Hoxton Hub**				**t-test**
	Min	Mean	Max	Stdev	Min	Mean	Max	Stdev	p-value
VA	1.4	3.6	7.1	1.5	2.6	6.4	14.6	2.6	<.0001*
Focimeter / AF	0.3	0.8	1.6	0.4	0.9	1.9	5.2	1.0	N/A
ORA	1.0	2.8	6.0	1.4	0.7	2.5	6.2	1.4	0.184
HFA	8.6	14.2	21.3	3.1	8.1	14.2	22.5	3.5	0.987
OCT	3.3	8.1	18.9	3.4	3.0	6.1	14.9	2.8	<.0001*

Table 2. Duration of diagnostic activity by station type (95% trimmed range) showing the minimum, mean, maximum and standard deviation (all in minutes) for Cayton Street and the Hoxton Hub. Results of a t-test comparing significant differences between the two sites are included with highly significant results ($p<0.01$) shown in red.

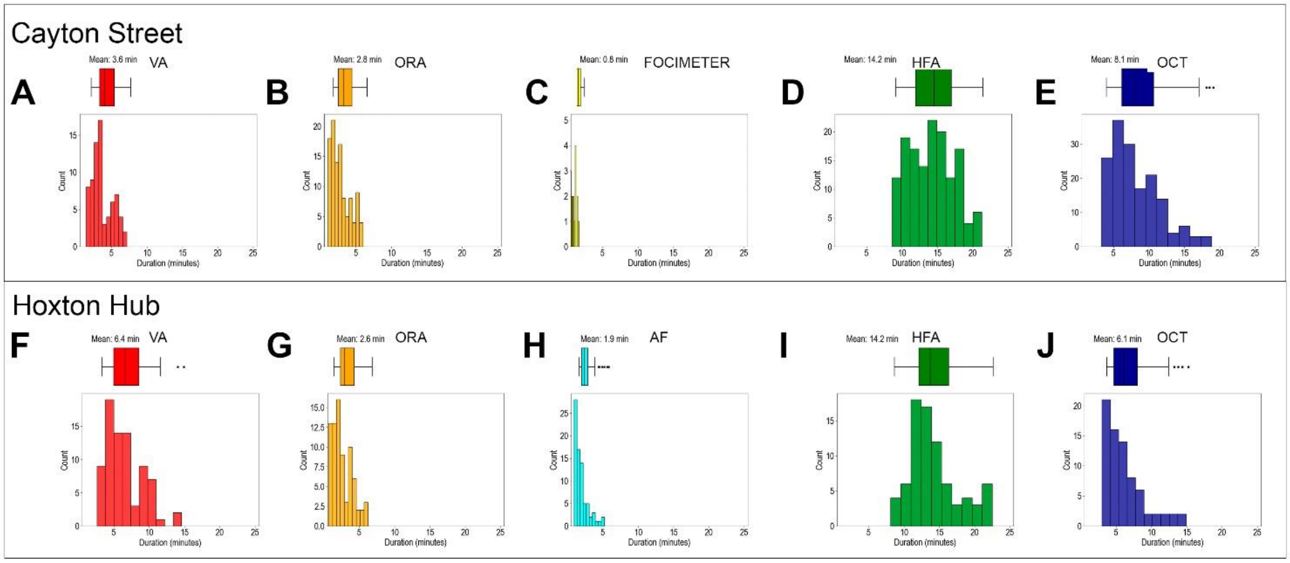

Figure 5. Distribution of duration of diagnostic activity (95% trimmed range) by station type in Cayton Street (a-e) and Hoxton Hub (f-j) on the same scale axis.

As expected, the VA, focimeter, AF and ORA tests were quick tests with averages ranging from less than a minute (0.8 min for the focimeter) to 3.6 min for the VA test in Cayton Street (table 2), which suggests that technicians were working very effectively. The VA test in Hoxton was significantly longer with an average of 6.4 minutes which was considered long by clinicians. This was mainly driven by some exceptionally longer cases reaching a maximum of 14.6 minutes (table 2 and figure 5f). Such outliers are often caused by elderly patients assisted by a caregiver, those with cognitive issues or new patients who cannot hear well so the technician has to repeat instructions. The OCT and HFA tests were longer overall with an average of 8.1 minutes and 14.2 minutes in Cayton Street and 6.1 minutes and 14.2 minutes in Hoxton respectively. The duration of the OCT exam in Cayton Street was significantly longer than the one in the Hoxton Hub.

In order to unpack the observed differences in durations of diagnostic activities between the two clinics, we plotted each patients' diagnostic activities as stacked and colored bar charts, showing time on the y-axis (figure 6a and b). This illustrates when each patient started with their first activity, the order they went through the diagnostics, the time they spent at each station, as well as waiting times in between (shown as gaps).

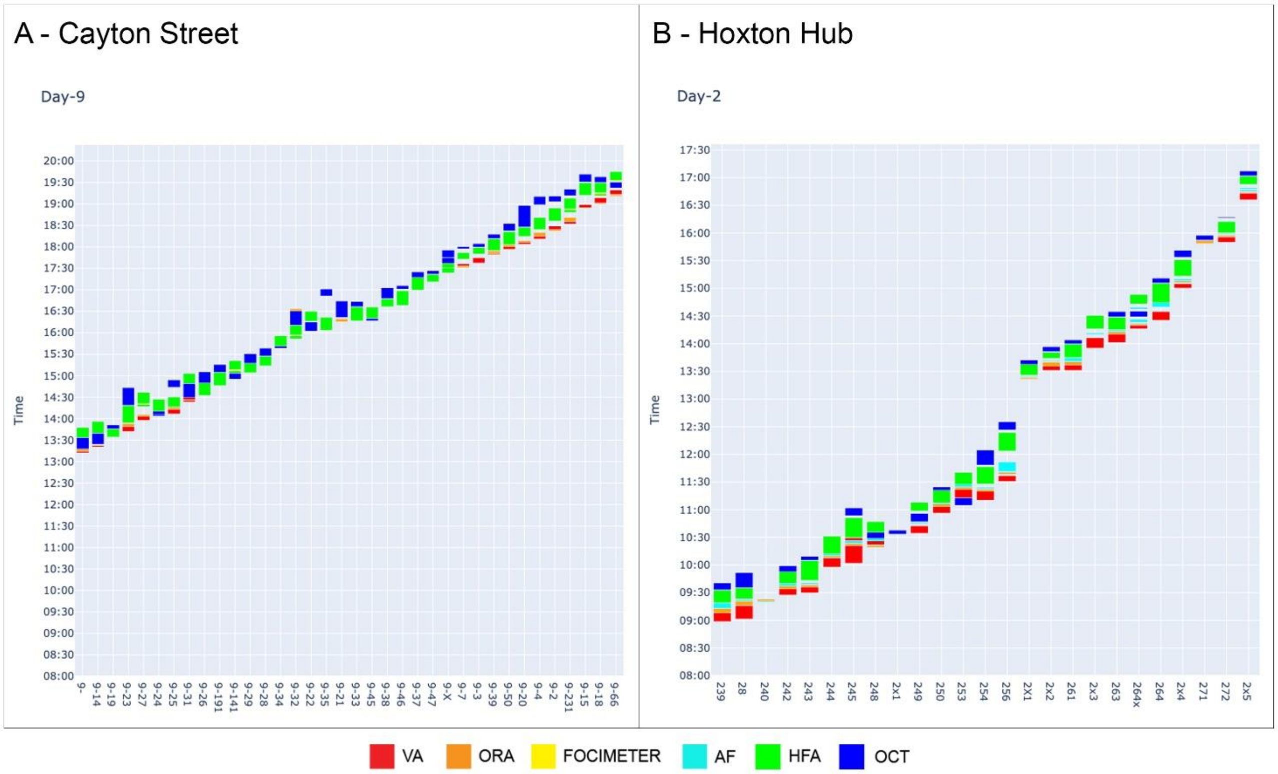

Figure 6. Bar charts of patient flows for selected days in Cayton Street (a) and the Hoxton Hub (b) with patient ID on the x-axis and time of day on the y-axis. Each column represents a single patient for a selected day of observations with activities colored according to the stations (red: VA, yellow: focimeter, cyan: AF, orange: ORA, green: HFA, blue: OCT).

It becomes obvious that the Cayton Street clinic experienced some bottlenecks and associated waiting times to access HFAs and OCTs as shown in figure 6a. In contrast, waiting times at the Hoxton Hub were not that much of an issue.

In addition to the differences in spatial layout and machine provision, which may have partly played a role here, especially as room 2 in Cayton Street was lacking an OCT and only two OCTs were provided versus three in the Hoxton Hub, the patient load for the two clinics also differed. Overlaying all stacked bar charts as those shown in figure 6 for all observed days highlighted that the Hoxton Hub was populated by a maximum of four patients at any point in time with an average of just 3.8 patients in the clinic simultaneously if calculated in 15-minute slots. In contrast the peak in Cayton Street reached seven patients with an average of 4.3 patients present at any 15-minute slot in time. This means that Cayton Street was busier than the Hoxton Hub with significantly larger peaks but also a higher throughput on average.

Busy shifts also resulted in changing clinical practices, as evident in figure 7, which plots the same two days as figure 6 but this time coloring activity durations by technician. In both clinics, a technician generally stayed with the patient throughout the whole exam process to help them with the tests. This can be seen on the bar chart where each color indicates a different technician. However, when Cayton Street became very busy, as in the late afternoon (see figure 7a top corner), technicians began to handover patients to other technicians so that they could in the meantime serve other patients instead of waiting alongside patients for the remaining stations to become available.

So as expected, fewer patients in parallel in Hoxton resulted in less turbulence, a more patterned order of examinations and fewer delays for existing patients, yet a lower throughput of patients overall.

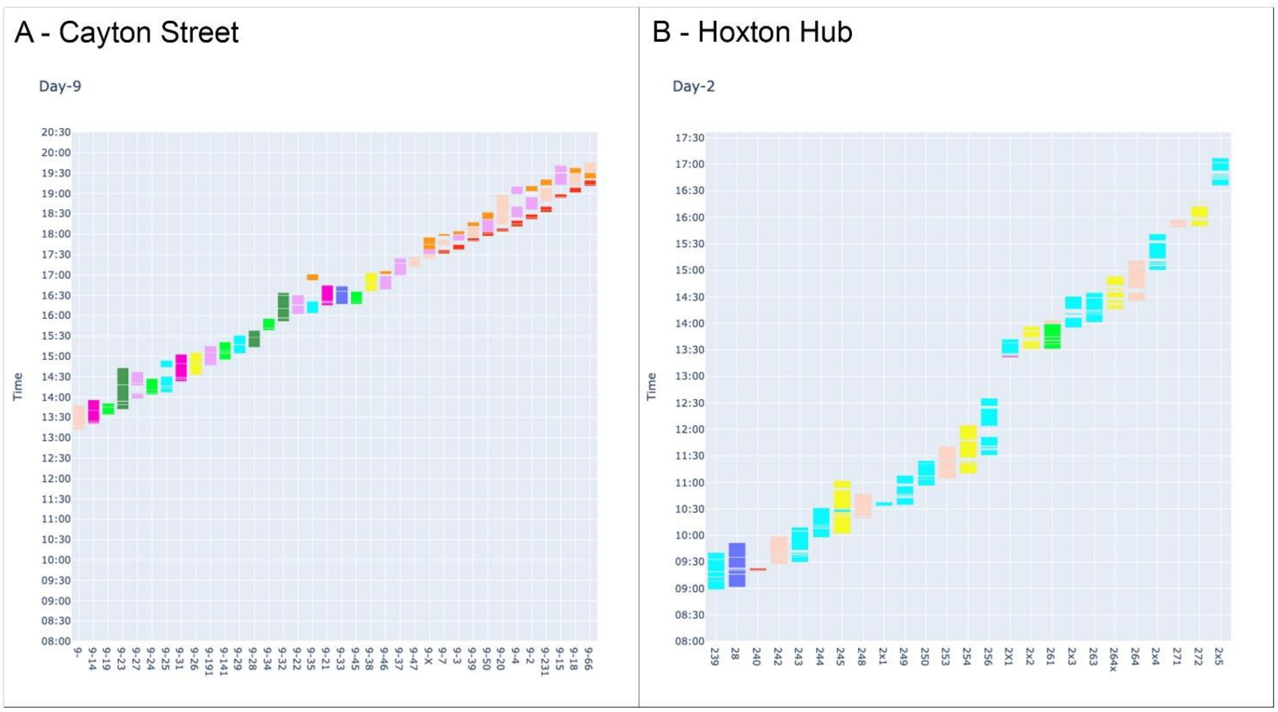

Figure 7. Bar charts of patient flows in Cayton Street (a) and the Hoxton Hub (b) with patient ID on the x-axis and time of day on the y-axis. Each column represents a single patient for a selected day of observations with activities colored according to the technician serving a patient.

Implications of the spatial layout of the clinics for patient flow

Bringing insights from both previous sections together, it can be seen that the spatial layout has implications for the patient flow.

The lane structure of Hoxton with its spatial ordering of stations results in more patient journeys completed in exactly that order, i.e., VA, ORA, AF, HFA and OCT last (see figure 6b again), thus sticking to the ostensive routine as explained by the clinical team. In contrast, the open-plan layout with no clear spatial ordering of stations results in a more variable order, which can be particularly seen in HFA and OCT switching positions frequently (figure 6a).

The overarching spatial logic in the patient flow of both clinics can be seen even more clearly when patient journeys are plotted from entrance to exit via all stations in a Sankey diagram (see figure 8a-b).

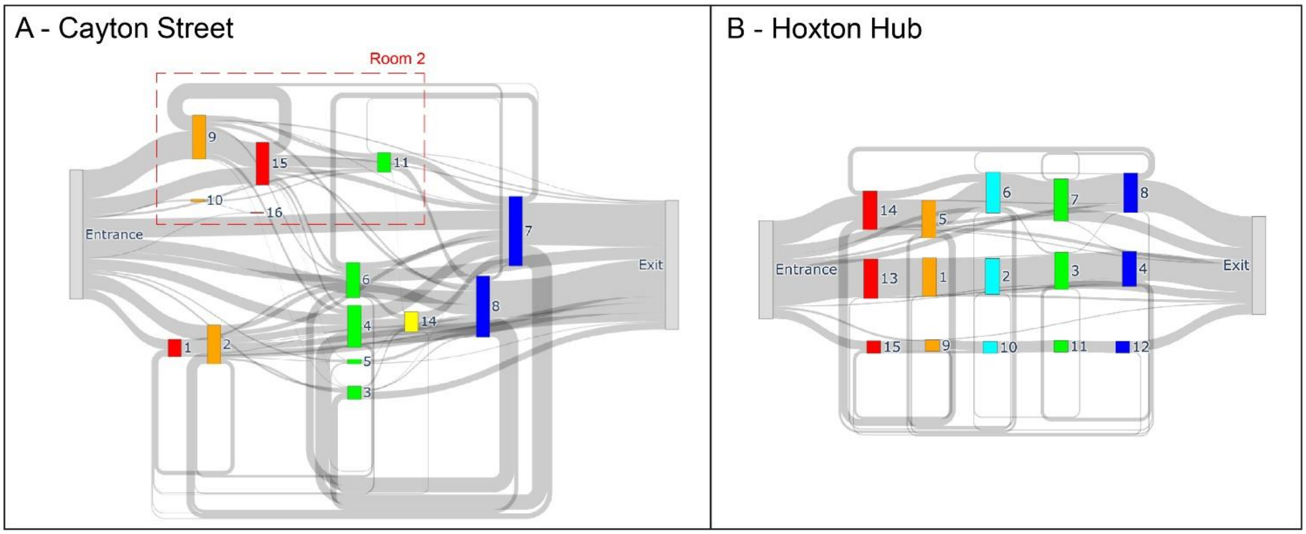

Fig 8. Sankey diagrams of patient flow in Cayton Street (a) and the Hoxton Hub (b). The thickness of the grey lines corresponds to the number of patients being transferred from one station to the other. Stations are colored by type (red: VA, yellow: focimeter, cyan: AF, orange: ORA, green: HFA, blue: OCT). Station numbers correspond to the detailed plan in figures 3a-b. Room 2 in Cayton Street is marked with a dotted red line.

In line with the linear spatial logic of the Hoxton Hub, the patient flow followed the spatial configuration of the lanes with very little movement between lanes (figure 8b) while Cayton Street performed in a much more organic way with more loops that highlight an order deviating from the ostensive routine. The main spatial structure of the two rooms of Cayton Street is visible in the flow diagram, too (figure 8a), with stations 9, 10, 11, 15 and 16, placed in the smaller Room 2 being more interlinked with each other than the remaining stations of the same type (1, 2, 3, 4, 5 and 6). The transfer from Room 2 to Room 1 mostly happens to access the OCT stations (number 7 and 8), which were not provided in Room 2. So generally speaking, journeys starting in Room 1 remained there, whereas those starting in Room 2 had to switch spaces.

Naturally, in both clinics, where possible, the next available station in easy reach and within line of sight was preferred, rather than switching rooms or lanes unnecessarily. This may seem obvious at first but essentially highlights the importance of line-of-sight relations among the stations within a patient journey.

Within a lane of the Hoxton Hub lines of sight are guaranteed, as shown in the step depth visualization (figure 4d), where intervisibility within the middle lane is highlighted, therefore making the transfer obvious not just for the patient but also for the coordinating technician. In contrast, lines of sight are not always guaranteed in the Cayton Street clinic, particularly in the set-up we observed with two separate rooms being in use. The visibility between the two rooms was obviously restricted. The step depth visualization (figure 4a) shows the visual distances from the ORA station number 2 (shown on the floor plan of figure 3a). From there, two visual steps are needed to reach Room 2, meaning that a technician had to look around the corner twice to see what was happening in the other room.

This complicates the job of the technician. Imagine starting in Room 2 and completing the first few steps of the patient journey there, but then in order to complete the OCT, the room had to be left. Without line-of-sight access, a technician might have to leave the patient, go around the corner twice and might find both OCTs occupied, in which case the patient would be led back to the waiting area. Imagine then that an OCT might become available again a minute later, the technician might not immediately notice, because they would have already started a new patient on their journey, again in a different room. This complication clearly resulted in delays and waiting for some of the patients who had to switch between rooms.

This might lead to the assumption that the lane structure was preferable, however, it has to be kept in mind that the Cayton Street clinic was busier. While waiting times mainly occurred in the Cayton Street clinic during our observations, this was clearly due to the Hoxton Hub seeing fewer patients than anticipated. The more uneven provision of machines evident in Cayton Street (five HFAs, the longest activity, but only two ORAs for example) suited a busier clinic well since not every activity took equally long, and therefore the clinic was better prepared to cope with high patient throughput.

How exactly different configurations and numbers of stations compare is revealed in the final results section.

Results from the queuing simulation: Arranging stations differently

The queuing simulation enabled us to isolate the potential roles of clinic workload intensity, resource allocation across the five activities and ostensive process flows through activities from the effects of spatial layout, lines of sight and clinic-to-clinic differences in the equipment used for specific activities and case-mix that may have affected activity durations.

Diagrams of the four ostensive processes we considered in the queuing simulations are shown in figure 9. All four impose the same order in which activities are conducted. They differ by whether stations are organized in lanes as per Hoxton with patients staying throughout in the lane they join (ostensive processes 1&2), by whether some activities are grouped with a new patient only starting the first activity in a group once the previous patient has completed the final activity in that group (ostensive process 1) and by the use of optimization to choose the number of stations devoted to each activity (ostensive process 4). Ostensive process 1 was used to reflect a proposed workflow, whereby technicians at the Hoxton hub would take a patient through the first three activities and then hand them over to another clinician who would take them through the last two activities. Note that this workflow was not observed in data collection.

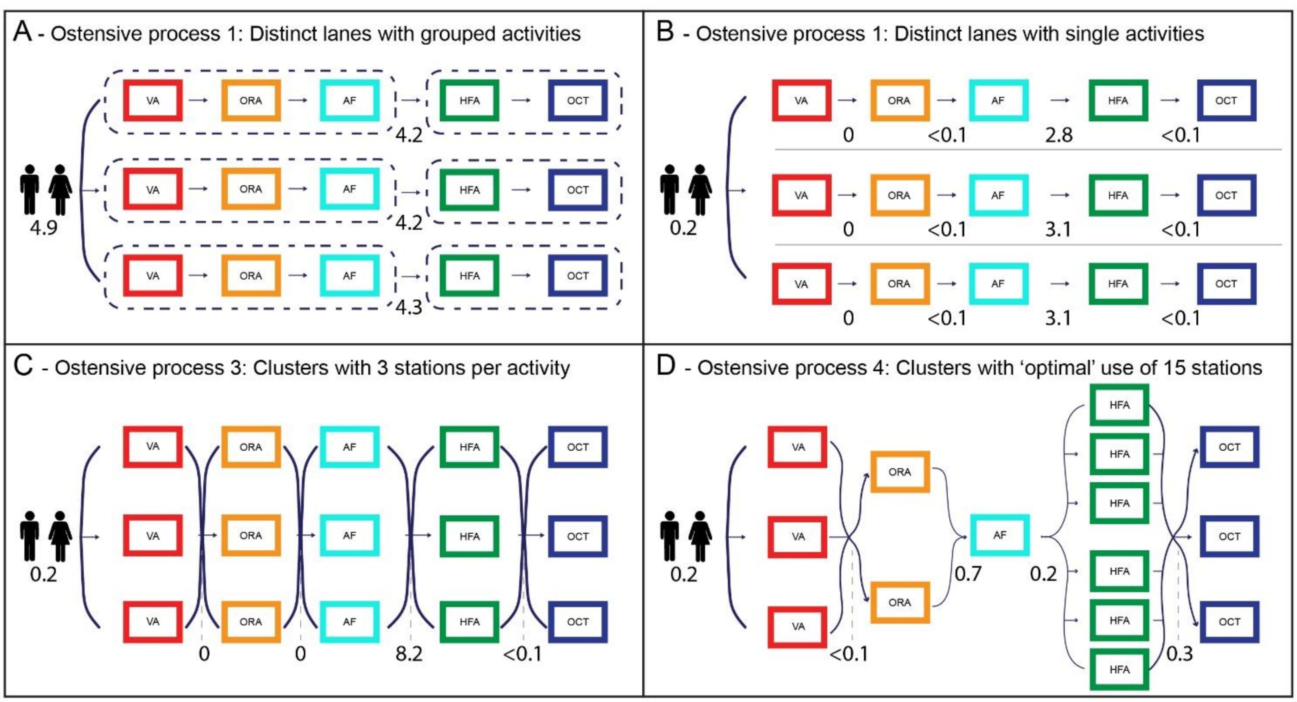

Figure 9a-d: Diagrams illustrating each of the four ostensive process flows considered in the queuing simulations. The numbers denote average queue sizes in simulation experiments with 60 patients arriving in batches of three every 10 minutes.

Because of these differences in structure, any queues will build up at different points in the process. The diagrams in figure 9 are annotated with the average queue sizes obtained from simulating operation of the clinic under that ostensive process with 60 patients arriving in batches of three every 10 minutes.

As another way of assessing the intrinsic efficiency of the different ostensive processes, figure 10 shows the simulated clinic duration for each ostensive process for a range of workload intensities.

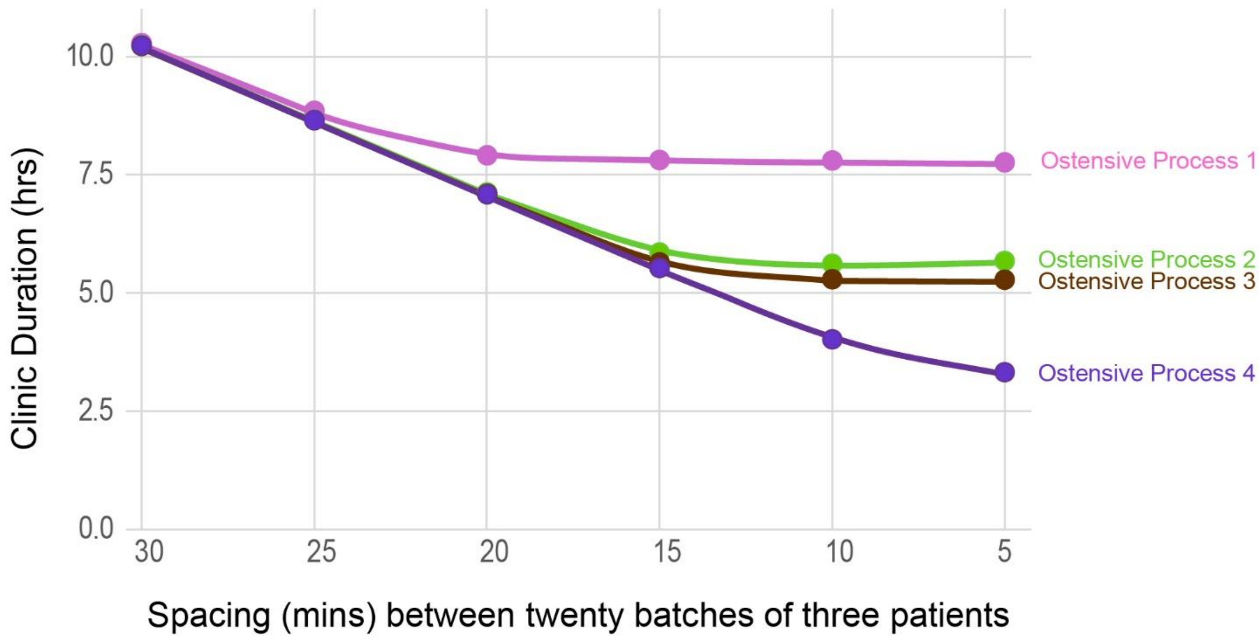

Figure 10: Plot of overall clinic duration for the four ostensive processes for different appointment spacing times.

We can see from figure 10 that, at very low workload intensities, overall clinic duration is the same for all ostensive processes. At higher workload intensities (with batches of patients arriving at shorter intervals) differences in the intrinsic efficiency of the process designs emerge, with the shortest clinic duration achieved using the allocation of stations to activity derived from the analytical optimization and with no use of lanes. Ostensive process 3 (clusters of three stations devoted to each activity) is marginally more efficient than process 2 (three stations devoted to each activity but divided into lanes) but with performance constrained by the considerable bottleneck at HFA. Ostensive process 1 is inevitably the least efficient use of stations as stations are kept idle while a patient completes all activities in each group.

Discussion

Reflecting on the results, four distinct themes warrant further discussion: bringing spatial and operational perspectives together, the importance of lines of sight, ideal setups in clusters or lanes, and ostensive routines and performativity.

Bringing spatial and operational perspectives together

In our approach we followed calls from the literature (Halawa et al., 2020; Jia et al., 2023) to bring spatial and operational perspectives together to understand decisions taken in clinical practice more holistically.

Building on extant literature using both approaches consecutively (Morgareidge et al., 2014), we integrated our analyses one step further by using the data set that is considered outcome variable in the space syntax paradigm, i.e., the data collected on diagnostic activity times as input to the operational model. Using detailed usage patterns of real-life cases adds the necessary accuracy to model everyday practices and not just assume idealized activity times.

From a clinic design perspective, both disciplines offer relevant insights as to how a clinic could be run more effectively, and by considering spatial and operational results alongside each other, more nuance is afforded. Our data set on diagnostic activity times added insight to ongoing discussions within the clinical teams at Moorfields, by highlighting how the services actually performed, thus contributing to evidence-based practices in general (Criado-Perez et al., 2020; Halawa et al., 2020; Mahmood, 2021) and to the evidence-based practices in place at Moorfields (Kotecha, Baldwin, et al., 2015; Kotecha, Bonstein, et al., 2015).

The importance of lines of sight

In addition to the well-documented effect of spatial propinquity to affect social behaviors (Small & Adler, 2019), visibility as the underlying spatial property expressing human perception (Wiener et al., 2007) is a fundamental aspect of how humans navigate the world (Gath-Morad et al., 2024; Gath-Morad et al., 2021). The ability to see what is going on in a healthcare setting has been clearly established as relevant in the literature, supporting not only nurse communication and coordination (Zook, Culpeper, Worley, & Miller, 2024) but also processes of care (Ossmann, 2022; Pachilova & Sailer, 2022).

Our analysis built on these literatures and showed that patient flows were eased by line of sight in those places where it was provided but also hampered by the lack thereof, particularly when stations were placed around several corners and therefore not easily accessible to coordinating technicians.

Visibility and open-plan layouts in particular can have negative effects, too, for example on perceptions of privacy as evident from a large body of work on workplace environments (Kim & de Dear, 2013; Parkin, Austin, Pinder, Baguely, & Allenby, 2011; Sailer et al., 2021), so a balance is required. Given the small-scale nature of the clinics and the unobtrusive nature of ophthalmic diagnostic activities, privacy concerns can perhaps be considered secondary.

The key take-away here is that a combination of privacy and line of sight is possible in ophthalmology, for example by using shoulder height partitions, and some materials engineering to manage sound.

Clusters versus lanes

In considering the detailed spatial arrangements of the interior layout of ophthalmology clinics, we go further than extant literature which focused on more large-scale configurational choices such as the study of centralized versus decentralized services (Hua, Becker, Wurmser, Bliss-Holtz, & Hedges, 2012; Salonen et al., 2013; Schaumann et al., 2019).

Lanes seem an obvious choice at first sight as they provide a clearly ordered patient flow, translating an ostensive routine most clearly into a spatial layout and therefore helping both patients in orientation and technicians in coordinating and overseeing flows. By virtue of their layout, lanes provide an obvious solution to the problem of sightlines, at least partially, since only one station of each type is visible within the confines of the lane.

However, beyond the consideration of lines of sight, a key restriction of using lanes is that one has markedly less flexibility in the number of stations allocated to each activity. The improvement offered by ostensive process 4 over the other process designs considered in the queuing simulations comes directly from exploiting the flexibility available when moving away from lanes.

While clusters are operationally more effective than lanes, their detailed spatial arrangement is a crucial consideration. Splitting services across multiple rooms creates issues as the line-of-sight relationship is broken. Ideally, all activities would be offered in a single room with intervisibility between all stations, however, this puts pressure on hospital real estate as traditionally smaller exam rooms are the prevalent configuration and finding a single space that comfortably fits 15 stations with perfect intervisibility from each station to every other one might be constrained by the reality of spaces on offer.

Ostensive routines and performativity

Building on our data of the variability of the order in which patients undergo diagnostic activities, interesting reflections on the difference between real-life cases and abstract conceptualizations of care processes are afforded.

In practice, clinical teams usually rely on their intuition and experiences of how to arrange outpatient clinics, as typically evidence-based design insights are still rare and often focus on patient experiences in hospital wards (Ulrich, Quan, Zimring, Joseph, & Choudhary, 2005; Ulrich et al., 2008). Processes of patient flow are therefore typically expressed and understood in their idealized form as an ostensive routine, which then gets designed into the process flows, the management practices of clinics and the spatial layout. The work of organization science scholars, however, has highlighted that ostensive routines are only a starting point, and that variability and change is the norm in many organizations (Feldman & Pentland, 2003; Feldman et al., 2021), thus leading to the insight that performative routines and dynamics are equally important to consider in healthcare contexts (Pentland, Recker, Wolf, & Wyner, 2020; Pentland, Vaast, & Wolf, 2020; Sailer, 2024).

This paper contributes to this discourse by showing that the ostensive order of the diagnostic process is varied in practice, following spontaneous decisions by technicians on the ground, and often resulting in improved effectiveness, for instance through better communication, or reduced waiting times.

Conclusions

This paper compared two ophthalmology diagnostic and monitoring clinics operated by Moorfields Eye Hospital to understand how their spatial structures and operational set-ups supported the flow and throughput of patients. We found that the two sites differed significantly in their spatial configuration (lanes versus clusters) but also in line-of-sight relationships among relevant stations in the patient journey (direct visibility versus looking around several corners); that diagnostic activity durations differed across the two sites for some activities (visual acuity longer in the Hoxton Hub, OCT longer in Cayton Street); that the presence of more patients in parallel caused waiting times (mainly in Cayton Street) but also a shift in practices with more patient handovers from one technician to another; that the lane structure resulted in fewer deviations from the ostensive routine; and that a different allocation with clusters of stations by type would result in process efficiencies (shorter clinic hours for the same number of patients, hence higher throughput).

Limitations were, firstly, that isolating spatial design as a variable is always difficult under real-life circumstances. The comparison between the two sites allows for a study of different spatial configurations but due to the practicalities of how the clinics were operated, certain biases could not be ruled out. For instance, the Hoxton Hub was newer and was run by newly recruited staff with less experience. In addition, we observed a rather quiet period for the Hoxton Hub, so we were not able to understand how the lane system would have fared under a heavier patient load. The queuing simulations made up for this limitation to some degree.

Secondly, being able to study different spatial micro-configurations of diagnostic activities within the same spatial envelope, and thus to intervene in the spatial design more directly while monitoring the impact on patient throughput as well as patient and technician experiences would be a fruitful endeavor.

Thirdly, more details on the nature of waiting would have been useful to have, both in the form of extended qualitative notes but also in the shape of a more systematic observation of exam durations. We used the process of sitting down and getting up from a seat as the signifier of the start and end of the diagnostic activity but in the observations, it transpired that some seats remained occupied after the end of the actual exam, as the follow-on station in the ostensive process was not yet available. This might explain the longer activity duration for the OCT in Cayton Street, which was affected by changes in order between HFA and OCT and emerging waiting times when the clinic was busy. Therefore, distinguishing between occupying a seat and actual exam durations in the observation protocol would be useful in future research. It is worth noting that the queueing simulations were based on observations from the uncongested Hoxton hub and so would be largely unaffected by this effect. The use of sensors or a comparison with machine time stamps might be useful, too.

Finally, microsimulation and analytical optimization could be built on. While our description of clinic operation derived from our observations include how technicians staffing the clinics manage the work, the microsimulation and analytical optimization do not evaluate ostensive process designs in terms of staff utilization and, with the focus very much on the allocations of stations to activities and division of stations into lanes, do not incorporate staffing constraints. This incomplete picture gives a particularly harsh assessment of ostensive process 1, the only argument for which is based on staffing. In addition, our modelling assumes a strict ostensive order, however, in practice more or less performativity of routines is the reality. This might call for more complex simulation models.

To conclude, this paper constitutes a first step towards an evidence-based practice of designing and organizing ophthalmology outpatient diagnostic and monitoring clinics in a way that enables a fast and efficient triaging of patients in order to decrease the backlog in NHS appointments in the UK, based on insights from architectural scholars and operation research.

Supporting Information

S1 file – Observation protocol
S2 file – Pseudocode for the queuing simulations
S3 file – Distribution of activities

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Supplementary material S1

Sailer, Utley at al.: Lanes, Clusters, Lines of Sight

Observation protocol

Project Name: Reconfigurable Diagnostic Hubs

Primary Investigator: Prof Kerstin Sailer, k.sailer@ucl.ac.uk

Project Aims: The project is set up to investigate the current practice of eye examinations at Moorfields Eye Hospital with the aim of optimizing the flow of patients in time and space. In addition to their Cayton St site, a new hub in Hoxton was opened in January 2021 to catch up with the Covid-induced patient backlog. Clinicians report that neither site runs optimally, as examinations take longer than expected, yet it is not known where time is lost. Based on observations, space syntax modelling and queueing simulation flow models, the aim of the project is to provide spatial and temporal configurations that are time-efficient and adaptable to different settings.

Aims of the Observations:

The aim of the observations is to study current journeys of glaucoma patients through space with detailed timings of examinations on different stations both in Cayton St and Hoxton. Two types of observation methods – journey observation and zonal observation, will be used to understand patient examination times and 3 trained research assistants (RAs) will be gathering data for a period of 3 days on each site. The collected information will help to identify causes of delays in the examination process which could be spatial, technician-related or patient-related.

Ethics and Risks:

Data will be captured on tablets which will cause no risk to the observers or participants. The RAs will receive NHS honorary research contracts and would be offered a Covid vaccine in order to minimize risks. A full risk assessment on UCL RiskNet has been produced and approved by Christoph Lindner, Dean of the Bartlett on 7/5/21. The research is exempt from NHS ethical approval as it falls under the category of service improvement as confirmed by the Moorfields clinical team.

Risks on Site

Do not take unnecessary valuables and keep tablets / mobile phones stowed away when outside. Bring food and drinks. Make regular breaks.

Sites for observation:

Cayton St: Cayton Street Clinic, Moorfields Eye Hospital, 4-12 Cayton St, London EC1V 2NT

Hoxton: Moorfields at Hoxton, 1&5 Bracklyn Street (Off Eagle Wharf Road), Hoxton, London N1 7TX

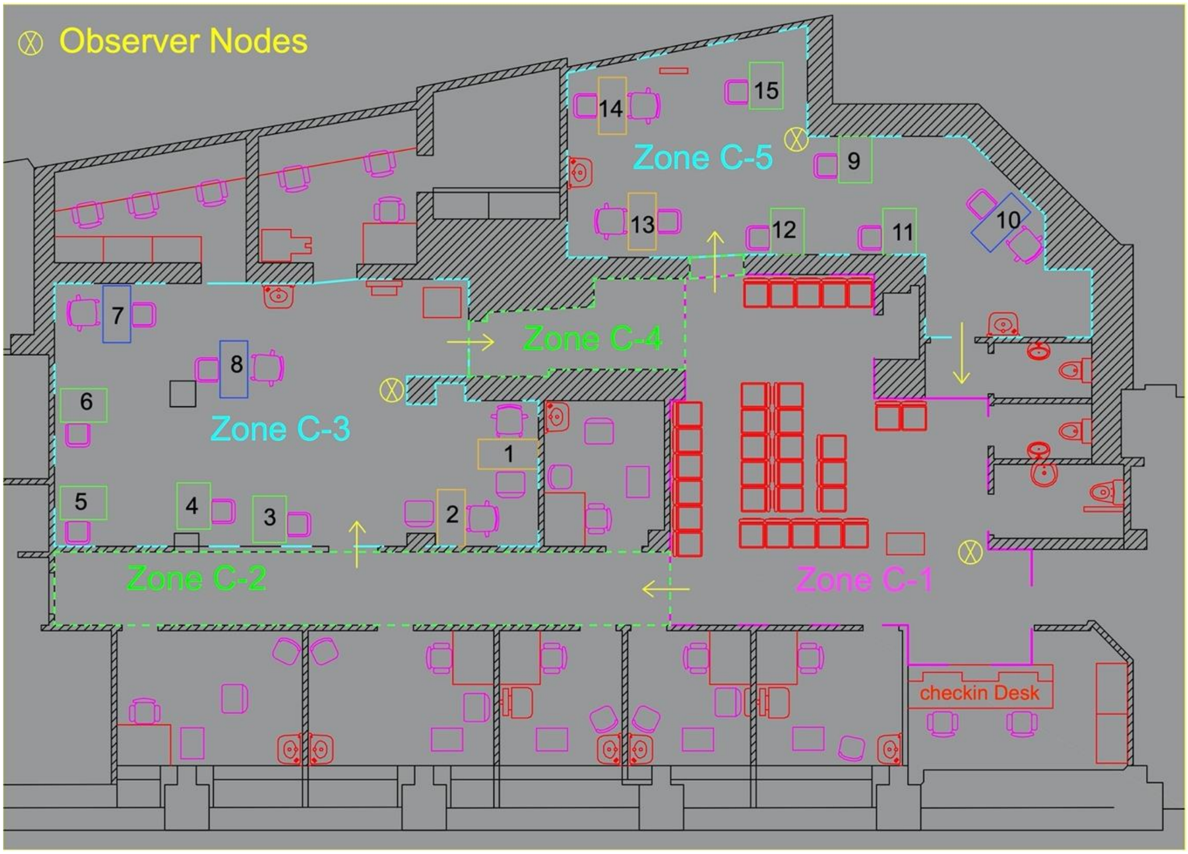
Dates of observation:

Hoxton: 23 June – 29 June 2021

Cayton St: 24 June – 6 July 2021

Observation Instructions

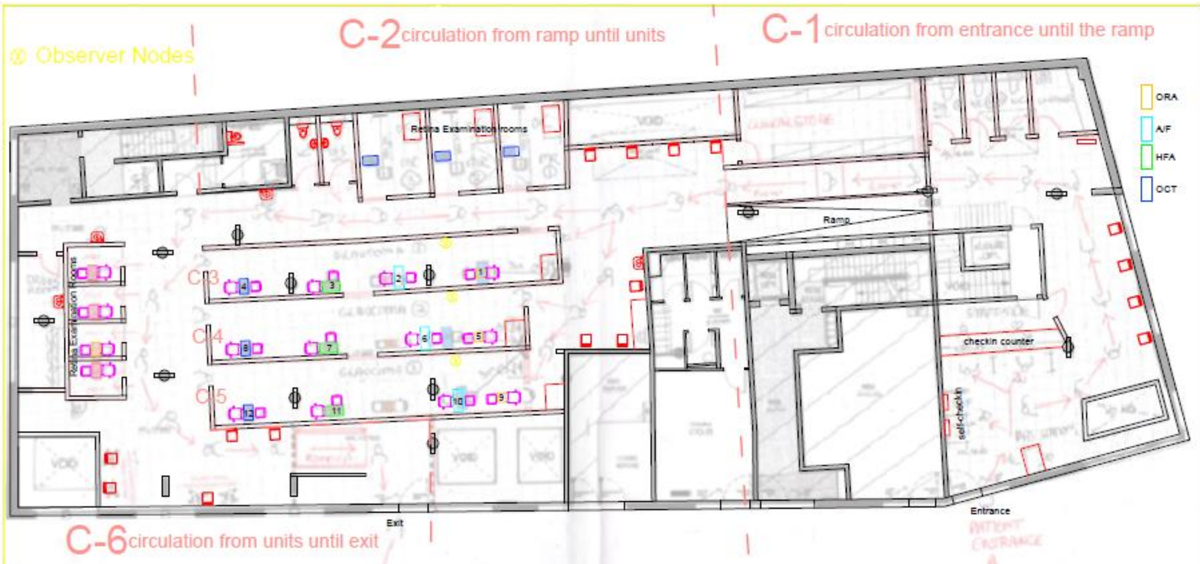
1. Cayton St Spatial Layout



The Cayton Clinic has three main zones: waiting area (C-1), room with eight stations (C-3) and another room with seven stations (C-5). Stations are numbered from 1 to 15. There are two corridors (C-2 and C-4) which connect the spaces. The circulation is expected to be one-way in theory, starting from the waiting area (after checking in), proceeding to C-3 through C-2 corridor, then C-5 through C-4 corridor and ending at the waiting area again (following the yellow arrows on the floor plan). Please see the floor plan for more details.

For the zonal observations, each observer will be allocated a zone to observe stations (Zone C-3 and C-5). An observation node on the floor plan indicates the position of the observer during observations for each of the zones. These are the best spots to see all stations in each zone, while not hindering movement or interfering in diagnosis. Observers need to be careful around patients and keep a reasonable and safe distance.

2. Hoxton Spatial Layout



Hoxton has examination stations arranged in three lanes (zones C-3, C-4 and C-5), an entrance zone C-1, a circulation zone C-2 and an exit zone C-6. Entrance and exit are separate, so there should be a relatively clear one-way circulation in place.

For the zonal observations, each observer will be allocated a lane to observe stations (Zone C-3, C-4 and C-5).

3. Types of Observations

There are two main types of observations conducted in this research.

Journey observations:

In this type of observation, the observer follows a patient throughout their journey from the check-in point, proceeding to the waiting area, moving from one station to another, reporting for check out and then leaving the premise. Of interest is how long each patient spends at a station and how long and where they spend waiting in-between stations. On a typical visit to the clinic, a patient has four consultations that take place at four different stations. This type of observation is meant to be also qualitative so please take as many notes as possible.

An example of the observation spreadsheet for this type of observation is shown below. Each line in the excel sheet of the journey observation represents what happens at one step of the process. The observer starts a new line whenever the patient moves from one step to another. Section 4 provides a definition of each data entry column.

	A	B	C	D	E	F	G	H	I	J
1	Day	Shift	Patient ID	Location	Activity	Technician ID	Start time	End time	Patient English	Notes
2	1	AM	55	5	exam	JoSm	09:13:07	09:28:12	fluent	swift examination
3	1									
4	1									
5	1									
6	1									
7	1									
8	1									

Zonal Observation:

In this type of observation, the observer stands at one of the observer nodes indicated on the floor plan to observe all stations within the designated zone. Of interest is how long a patient spends at each station. All stations within the boundary of the zone must be observed simultaneously, with no need to go outside and see what happens before or after.

An example of the observation spreadsheet for this type of observation is shown below. Each line in the excel sheet represents one step of the process at a single station per observed patient. The observer starts a new line for every different process a patient undergoes at a station or the same patient at a different station. Section 4 provides a definition of each data entry column.

	A	B	C	D	E	F	G	H	I	J
1	Day	Shift	Patient ID	Location	Activity	Technician ID	Start time	End time	Patient English	Notes
2	1	AM	55	5	exam	JoSm	09:13:07	09:28:12	fluent	swift examination
3	1									
4	1									
5	1									
6	1									
7	1									
8	1									

What is a process?

The full glaucoma examination consists of four consecutive steps:

1) Pressure and vision (on a machine called ORA)

2) Measure eyesight (in Hoxton: on a separate station with a machine called Autorefractor; in Cayton Street on a mobile handheld device called viscometer, normally undertaken before step 3, but already at station 3)

3) visual field test (on a machine called HFA)

4) imaging (on a machine called OCT)

A process in the way we want to capture them in the observations is an eye examination step undertaken at one of the above-mentioned machines / stations. Transition times between stations, or between waiting area and stations are only captured in the full journey observations, but not during the majority of the zonal observations.

4. Definition of data entry in the observation sheets

Day

There are ten days of observations in total (1-10). This is constant and does not change on each sheet. The observer will be provided with different sheets for each day of observations.

Shift

There are three clinic periods during the day in Cayton Street: Morning (AM), Afternoon (PM) and Evening (EVE) and two in Hoxton (AM / PM). The observed needs to choose this value from the dropdown menu, based on which clinic period they are covering.

Patient ID

Every patient who enters the clinic for examination will be given a sticker by the receptionist with a ref number from 1 to 72 (which is the maximum number of patients per day in Cayton, the maximum number of patients per day in Hoxton is 50). Each observer needs to write down this number for each data entry. If a patient does not have a number, the observer needs to ask the receptionist to provide the patient with a number or ask the technician who accompanies the patient to help.

Location

Each station has a station ID displayed on the table. This value should be entered from the drop-down options. If the table does not have a label, please check the excel sheet tab 'check plan' which has the number of stations on the floor plan. Note: the stations in Cayton are numbered clockwise, starting from the observer's left-hand side if they are standing in their observer node (back against the wall). Hoxton stations are numbered linearly by lane.

For the journey observations corridors, toilets, waiting areas etc. are available from the drop-down menu.

Activity

For zonal observations, activity=exam in Hoxton, as we classify the whole length of the time that a patient sits on the chair of an examination station as 'exam'.

In Cayton Street, when patients approach station 3-6 or 11-14 (HFA), typically two processes will occur, one after the other, first the eyesight measurement (mobile device, called viscometer), then the field test (large machine). This means activity can either be 'exam' or 'exam visco'.

For journey observations, a larger number of activities are available from the drop-down menu, including check in, exam, wait_sit, wait_stand, talk to someone and other (toilet for example). The focus of all activity observations is the patient. Note: we do not capture walking as an activity, as we assume patients will be walking / be in transit from one process observed to another, so the difference in end time of one process and the start time of the next process will automatically be assumed to be walking. Therefore, if the patients are not walking, use another activity to capture what they are doing.

Technician ID

This is the ID of the technician accompanying each patient. Each observer needs to enter the first two letters of the technician's first name and the first two letters of their last name. Each technician has a name tag which is visible on their clothing. For example, a technician with the name 'Kerstin Sailer' will get an ID 'KeSa'.

Start time

This is the start of each process you are recording. As accurately as possible, note the time when the patient has sat down. This is not necessarily the time a patient comes near the station. The observer needs to use the formula '=now()' which will automatically generate the current time in the form of hour/minutes/seconds. Observers need to be very careful around this column and try to enter the data once and proceed to next columns. Each observer needs to take continuous screenshots of the recorded data during observations (as data backup). We recommend every half an hour. You could set up a reminder on your phone but please don't use sound as this may disturb people around, just a buzz.

End time

This is the end of each process/examination you are recording. Again, try to accurately capture when the examination is finished. This is the moment in which the patient leaves the seat. Do not include transition times or waiting times (standing) in the times recorded for the examination process. The observer needs to use the same formula '=now()' to enter the value.

Patient English

The observer needs to assess and record the fluency in English of each patient. Each observer can choose from four levels in the drop-down menu: 'fluent', 'few issues', 'many issues', 'translator'. For this, the observer should try to be attentive and overhear the dialogues that take place.

Notes

Please use this field to note anything you feel is worth recording. This could include notes on occurring delays, causes for waiting, etc. It could also include notes on the technician, e.g. when they have to leave the stations temporarily, etc.

5. Observation Schedule

Each observer will receive their own observation schedule. The schedules have to work around several constraints, i.e. Hoxton does not always have all three lanes open and Cayton Street has three shifts rather than two and on some half days they share their space with Urgent Care, hence we're avoiding those time slots.

Observers have to stick to their own schedule in order to cover the number of observations we need.

Times for journey observations are generally allocated at the start of observations, so that observers can familiarize themselves with the flow of the examinations. Breaks are scheduled regularly – they are indicative. Observers should aim to finish a set of observations before going on break. When break time is approaching during zonal observations, no new processes should be started, but all existing should be completed.

Note: each patient observation journey should take approximately 30-45min, so it is suggested to complete as many as possible in the allocated time slots.

6. Data Backup

Observers should log into the NHS Guest Wifi upon first arrival at the clinic and make sure the tablets are connected to the internet throughout.

Excel sheets save automatically on the tablets. Observers need to log into their Microsoft 365 account at the beginning (once) in order to edit and save data. Use 'save as' at the start of the day initially and choose your OneDrive as file location. This should save the file onto the cloud. Every evening when you get home, please locate the file in your cloud and email it to the project PI.

For an additional backup, please make screenshots regularly – this is particularly important for the time capture.

The Excel sheets have been programmed to not update cells automatically (important so that times are not updated every time a new start / end time is entered). Do not change anything in the settings / options.

7. General Rules of Observations

- Always wear your honorary researcher badge and a facial mask.
- Try to be discrete but attentive and record every required field of information.

- If you feel that you messed up a data entry, especially when it comes to timings and station IDs, please indicate this in the notes.
- The observer node is an initial suggestion. Please feel free to move discreetly to other spots which will facilitate your observations. However, be careful to not stay on the path of patients and staff or invade patient’s privacy.

Supplementary material S2

Sailer, Utley at al.: Lanes, Clusters, Lines of Sight

Pseudocode for the queuing simulations

The pseudocode below outlines how the queuing simulation operates for a single experimental combination of ostensive process and appointment schedule. Key variables are given in bold using a convention that ***variable_i*** represents a vector with elements indexed *i* and ***variable_j_k*** represents a two-dimensional array with elements indexed (*j,k*). The R code is provided.

1. Assign values to:

   NumRuns the number of simulation runs per experiment, indexed *r*

   Seed_r the random number seed to be used for run *r*

   NumPats *the number of patients given appointments, indexed p*

   NumActivities *the number of clinical tests patients undergo, indexed a*

   DNAProb *the probability that a patient does not attend.*

2. For the ostensive process considered, assign values to

   NumQueues – the number of queues for the ostensive process, indexed *q*

   a_q - the activity associated with each queue *q*

   NumServers_q – the number of servers (pieces of equipment) serving queue *q*

   NextQueue_q_s – the next queue joined by those served by server *s* at queue *q*

   TransitTime_q_s – the time taken to join next queue from server *s* at queue *q*

3. For the appointment schedule considered

   Form a set of patients $\mathbb{P}$ with patients indexed *p* = 1 to ***NumPats***.

   Assign an appointment time to each patient as per the appointment schedule.

   For all patients $p \in \mathbb{P}$, initialise ***NQ_p***, to 1 (the first queue they would visit under this ostensive process).

4. Initialise each run r:

   Set the random number seed to ***Seed_r***

   For each patient $p \in \mathbb{P}$ randomly sample a set of activity times from a collection of observed patient journeys.

For each patient $p \in \mathbb{P}$ determine attendance as a Bernoulli trial with probability of success (1-DNAProb).

Create subset $\mathbb{A} \subseteq \mathbb{P}$ of patients that attend the clinic.

For each patient $p \in \mathbb{A}$ sample a ClinicArrivalTime_p from their appointment time.

Set variable NextQueueArrivalTime_p to ClinicArrivalTime_p for that patient.

5. For each queue from q = 1 to NumQueues

   Form set $\mathbb{A}\_q \subseteq \mathbb{A}$ of patients p with ***NQ_p*** = *q*.

   Form vectors of *NextQueueArrivalTime_p,* activity times, and patient indices *p* from patients $p \in \mathbb{A}\_q$, with elements ordered by increasing values of *NextQueueArrivalTime_p*.

   Use queue_step() function from QComputer package to return

   DepartureTime_p for each patient $p \in \mathbb{A}\_q$

   s the identifier for the server used by each patient $p \in \mathbb{A}\_q$

   Use the average_queue() function from QComputer to return

   The average number of people in queue *q* for this run under this ostensive process and this appointment schedule. Store values.

   Set ***NextQueueArrivalTime_p*** = ***DepartureTime_p*** + ***TransitTime_q_s*** for each patient $p \in \mathbb{A}\_q$

   Set ***NQ_p*** = ***NextQueue_q_s*** for each patient $p \in \mathbb{A}\_q$

6. Take clinic duration for run r under this ostensive process and this appointment schedule as the largest value of NextQueueArrivalTime_p among $p \in \mathbb{A}$

7. Repeat steps 4 to 6 for each run up to NumRuns

8. Calculate average over runs of average queue size for each queue, and average over runs of clinic duration from stored values.

Supplementary material S3

Sailer, Utley at al.: Lanes, Clusters, Lines of Sight

Distribution of activities

The observed duration of activities is highly skewed with a small handful of very significant outliers, where the diagnostic process took much longer than anticipated. There are various reasons for this, including frail patients, those with cognitive issues or hearing loss thus requiring additional assistance. The way the data was captured may also play a role, since it was observed how long a station was occupied by a person sitting there, however, it might have been the case that the diagnostic process was completed, yet a patient remained at a station because the next station in the flow was not yet vacated.

In the paper, we report the 95% trimmed range to eliminate the outliers and show a more representative picture of typical diagnostic examination times.

For completeness, we report the full data set in comparison with the 95% trimmed range here.

In summary, the full data set shown in table 1 and figure 1 comprise a total of 1007 observations, whereas the reduced 95% trimmed data set highlighted in table 2 and figure 2 contains 896 observations. This means an overall reduction of 11% in data points. Notably, the t-test results remain stable, and all mean values also remain relatively stable with only slight variations (ranging from 1% for HFA examinations at Cayton Street to 14% for the much shorter AF examinations at the Hoxton Hub). This means the 95% trimmed range is representative of the full data set yet more true to what is typically happening in ophthalmologic examinations.

Full Dataset

Station	**Cayton Street**					**Hoxton Hub**					**t-test**
	Min	Mean	Max	Stdev	N	Min	Mean	Max	Stdev	N	p-value
VA	0.8	3.8	12.9	2.1	85	1.7	6.7	24.2	4.1	88	<.0001*
Focimeter / AF	0.2	0.9	1.9	0.5	26	0.7	2.2	11.9	2	88	N/A
ORA	0.6	3.2	32.2	3.1	122	0.3	2.8	10.4	1.9	86	0.266
HFA	5.4	14.3	24.5	3.9	159	3.9	14.4	30.9	4.9	89	0.896
OCT	0.9	8.6	42.5	5.3	179	0.8	6.6	24.1	4.09	85	0.002*
SUM					**571**					**436**	

Table 1. Duration of diagnostic activity by station type showing the minimum, mean, maximum and standard deviation (all in minutes) for Cayton Street and the Hoxton Hub as well as the sample size N. Results of a t-test comparing significant differences between the two sites are included with highly significant results ($p<0.01$) shown in red.

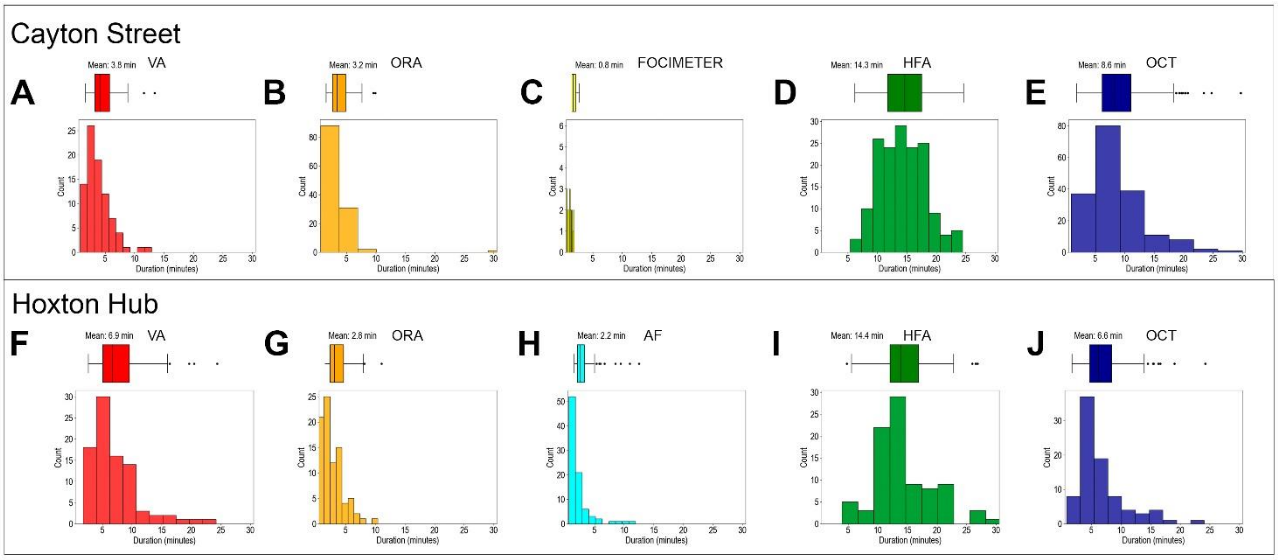


Figure 1. Distribution of duration of diagnostic activity (full data set) by station type in Cayton Street (a-e) and Hoxton Hub (f-j) on the same scale axis.

95% Trimmed Dataset

Station	**Cayton Street**					**Hoxton Hub**					**t-test**
	Min	Mean	Max	Stdev	N	Min	Mean	Max	Stdev	N	p-value
VA	1.4	3.6	7.1	1.5	75	2.6	6.4	14.6	2.6	78	<.0001*
Focimeter / AF	0.3	0.8	1.6	0.4	22	0.9	1.9	5.2	1.0	78	N/A
ORA	1.0	2.8	6.0	1.4	108	0.7	2.5	6.2	1.4	77	0.184
HFA	8.6	14.2	21.3	3.1	143	8.1	14.2	22.5	3.5	79	0.987
OCT	3.3	8.1	18.9	3.4	161	3.0	6.1	14.9	2.8	75	<.0001*
SUM					**509**					**387**	

Table 2. Duration of diagnostic activity by station type (95% trimmed range) showing the minimum, mean, maximum and standard deviation (all in minutes) for Cayton Street and the Hoxton Hub as well as the sample size N. Results of a t-test comparing significant differences between the two sites are included with highly significant results ($p<0.01$) shown in red.

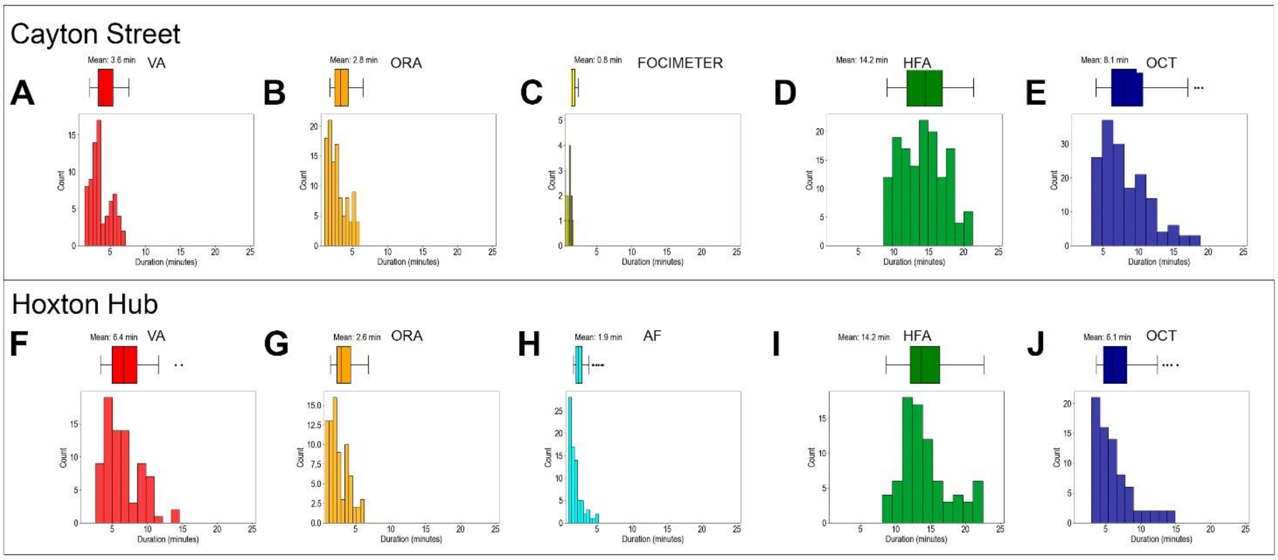


Figure 2. Distribution of duration of diagnostic activity (95% trimmed range) by station type in Cayton Street (a-e) and Hoxton Hub (f-j) on the same scale axis.