Understanding Patient Flow using IoT in a Pop Up Eye Clinic

D. Wilson, S. Gray, I. Eames & P. Foster
University College London, Gower Street, London WC1E 7JE, UK
d.j.wilson@ucl.ac.uk

Abstract. Ophthalmology typically records the highest levels of attendances for specialist outpatient treatments in the NHS with figures reaching 5.5 million visits for 2020-21. To catch up with a significant backlog of appointments due to COVID, pop-up eye clinics in shopping centres are being explored as an innovative way to increase capacity. Whilst design guidance for clinics exist, it tends to focus on the precedent of a hospital setting. This project used Internet of Things technologies to monitor patient flow on a per second basis through a clinic to understand from an end-to-end system perspective, opportunities for efficiency gains. In this paper we describe how the results of spatio-temporal analysis of 4000 patients and data from environmental exposure risk models informed clinic design decisions.

1. Introduction

Ophthalmology is a branch of medicine that deals with diseases of the eye. It involves the surgical and medical management of eye disorders. In the UK, ophthalmology typically records the highest number of outpatient attendances of any NHS speciality with appointment numbers reaching 5.5 million visits for 2020-21 (NHS Digital, 2021). During the COVID pandemic patients missed routine check-ups and examinations creating a significant backlog of appointments. To expand capacity and increase patient flow through these services, Moorfields Eye Hospital tested pop-up eye clinics (Mills et al., 2022) in decentralised easy to access locations as an alternative to traditional appointments in a central London hospital.

Glaucoma, macular degeneration, diabetic eye disease (i.e. medical retina) and cataract care at Moorfields consists of several standardised tests that each patient goes through when visiting an outpatient clinic. Measurements of visual acuity (chart reading) is carried out for all ophthalmology patients. Glaucoma is typically tested through a comprehensive eye exam that includes measuring the pressure in the eye, examining the optic nerve, and testing the visual field using equipment such as a Humphrey Field Analyser (HFA). Medical retina conditions are tested through an eye exam that includes examining the retina, macula, and optic nerve, using imaging devices such as optical coherence tomography (OCT). Cataract assessments include examining the lens, pupil, and cornea, as well as imaging tests such as OCT.

Traditionally, there has been a bespoke approach to testing for each patient, assuming it would be quicker. In this clinic a standardised testing menu was developed to test if smoothing the flow led to a more efficient process, even though more tests might be carried out. This means that the patients, and the technician running the procedures, go through very similar activities that have the potential to be optimised to reduce patient journey time and increase appointment availability.

Figure 1 shows an example flow of patients through a clinic based on 3 different pathways. The red lines show the flow of glaucoma patients, the green lines medical retina and the blue lines cataract. The same type of machine can be used on multiple pathways. It should be noted the site provided NHS service care, but a subset of patients consented for research level data collection, in the "Research" cubicles after attending reception and before departing.

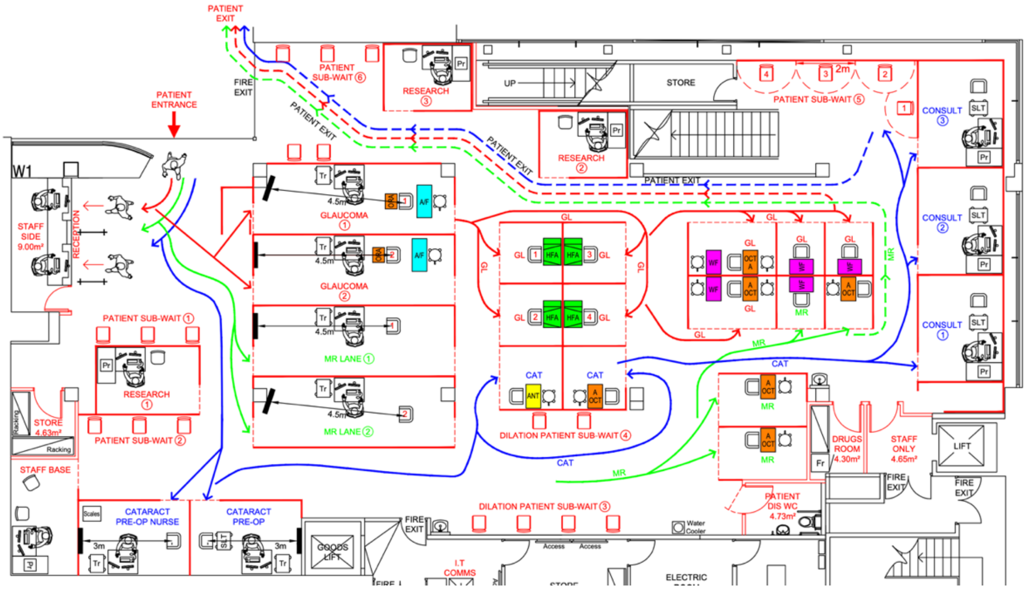


Fig. 1. Patient flow through clinic (Phase 4) glaucoma (red), medical retina (green) and cataract (blue)

This research extends existing space syntax studies (Sailer, 2021) which use a set of analytical tools to measure the spatial configuration of a given area and how it affects the movement of people. Driven by direct observation and ethnographic processes, space syntax is used to analyse the impact of design decisions on the flow of people, such as the placement of entrances and exits, the size and shape of pathways, and the presence of obstacles. The use of IoT technology in this research seeks to test automated methods for the tracking of 1000 people through a clinic versus direct observation of 10 patients. The hypothesis is that scaling observations 100x will generate novel insights regarding patient flow and provide quantitative evidence on the impact of different clinic layouts on visitor journey time. The second hypothesis is that the position and movement of people is a key factor in the spatio-temporal variation of air-borne hazards within real, complex spaces with the IoT approach providing the key data input into new models.

2. Experimental Environment

The clinic in a North London shopping centre retail unit provides glaucoma, medical retina and cataract care consisting of combinations of several standardised tests that each patient goes through when visiting an outpatient clinic. A key design feature of the pop-up clinic was reconfigurability, to allow testing of different layouts, in order to understand how they influenced patient throughput and enabled minimisation of infection risk throughout waves of COVID-19. The interior fit out used a novel, modular system of creating functional environments that could be changed over the space of a long weekend. This allowed changes in machine layout, numbers of machines and sequences of procedures. Figure 2 highlights privacy enabling “rooms” for private interactions (left), booths providing some isolation whilst allowing staff to see which machines are free (middle), and the dark booths (right) to provide a light-controlled environment for machines which require minimal background light. Four different layouts were tested in the pop-up clinic between October 2021 and February 2023.

To understand the performance of the clinic environment, two primary methods of automated data capture were used to make observations. They included patient tracking through Ultra-Wide Band (UWB) technology (Ubisense, 2022) and environmental measurements from air samplers located at locations throughout the clinic to assess particulate loading and sizes, temperature, humidity and CO_2 concentration over a working day. The purpose was to assess the spatial and temporal variation of air mixing and dilution within a complex space. A key ingredient in assessing air-borne hazards, particularly in relation to past experience of COVID-19, is how air, potentially laden with pathogens (contained within droplet nuclei, generated by breathing or an aerosol generating procedure) is dispersed and diluted. These processes depend on (a) location and movement of people by acting as sources of heat (which greatly affects flows), humidity and air-borne pathogens, (b) the clinic environment through layout and equipment (as sources of heat), (c) exchange surfaces (the entrance, other floors, air-conditioning units). In a real environment, all three elements are changing in time and the physical process of mixing, likewise, changes spatially and temporally. In this activity, we use fixed and mobile measurements of CO_2 and temperature, and link them (a,b) and (c).

Fig. 2. Photograph of clinic showing typical layout of machine booths.

Seventeen Ubisense UWB sensors located around the ceiling of the clinic support the real time location of 100+ credit card sized tags allocated for tracking. An example UWB sensor can be seen in Figure 2. Each tag is worn by a patient participating in the research and tracks their movement throughout their visit to an accuracy of 15cm. The technology works by transmitting a signal over a wide range of frequencies, allowing for greater accuracy and precision in tracking and locating objects. The signal received by the sensors are then used to determine the location of the tag carried by the patient. Each of the UWB sensors had a wired connection to a timing server which aggregates all the readings and saved all timestamped coordinate readings to a database in an on-premises server. A Ubisense application running on the same server provides a web-based interface to real-time and historic data.

A key requirement of automating the data capture of the patient flow was maintaining confidentiality of the research participant, a common challenge when using other technologies such as cameras or Bluetooth (Ziegeldorf et al., 2013). In addition, there was a requirement to provide information on patient journey as a vector through space which cannot be obtained through other traditional space occupancy systems which rely, for example, on passive infrared sensors (Azizi et al., 2020). To maintain patient confidentiality, the Ubisense system was setup so that each tag had a unique ID as a reference for the geolocation database. The Moorfields reception staff allocated the tag ID when the patient joined the research programme and the ID was stored in the patient record. This process isolated the non-NHS research team from any personally identifiable information.

CO_2/humidity/temperature were measured using 8 probes (Testo Probe 138, www.testo.com) placed across the clinic. The aerosol load was assessed using a Fluke 985 Particle Counter, but the aerosol generating activities within Brent Cross dominated the measurements. Data was recorded at every 10s from the start and end of the clinic. The air flow within the clinic was naturally ventilated and unfiltered; the aerosol loading was mostly dominated by aerosol generating activities within Brent Cross, with sub 2 micron aerosols being generated from a nearby road (A406).

Data from these technical platforms were validated against ethnographic observations following an individual patient through a complete journey and qualitative feedback from clinicians, technicians, and the design team responsible for the interior layout of the clinic.

3. Data Acquisition, Processing and Visualising Flow

The Ubisense web application provides an interface to download raw patient traces as CSV files. Table 1 shows a sample of raw data containing information on patient reference, an x/y location based on the Ubisense coordinate system and the time span at that location.

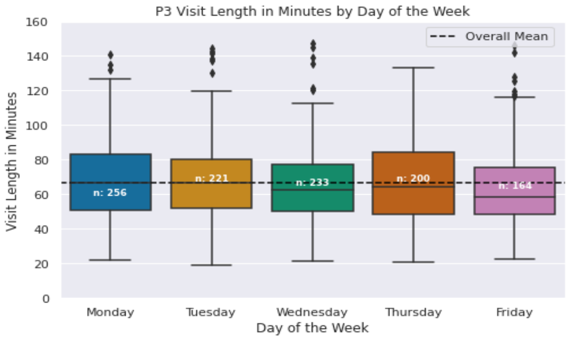
Table 1. Sample raw data from Ubisense.

Patient	**Location**	**from**	**To**
G1638	3.738,6.596	15/03/2022, 11:15:51	15/03/2022, 11:16:13
G1638	5.389,5.838	15/03/2022, 11:16:13	15/03/2022, 11:16:14

The downloaded raw position data is processed in Python to remove outlier tags and to generate derived variables. Examples of outliers include tags that had been allocated but not used, observable through very short journey times, or tags that show data beyond 3 hours, which implies tags that were not checked back in or left overnight. The derived values include extra columns of data such as visit length, hour of day, am / pm, pathway etc. A full description of the data cleaning process is documented in the project GitHub repository (Djdunc, 2023). The result is an output CSV used to generate the analysis below.

Basic statistics of patient flow through the process were plotted to show variations between both days of week and the 4 different layouts. This data provided the clinicians and technician with quantitative data on the performance of the different layouts in terms of total journey time. Since measurements were taken over several weeks the data also provided opportunity to observe “settling in” time to new operational layouts. Figure 3 shows an example box plot of total patient journey times across weekdays.

In phases 1-3 both staff and patients carried tags however the Ubisense system only recorded patient data. In phase 4 of the research, staff data was also recorded to support the analysis of relationships between staff / patient proximity. In all cases, the allocation of staff tags was random with no record of staff member to staff tag being recorded. In total approximately 1000 patients were recruited per phase which equated to roughly half of the patients volunteering to participate in the recording whilst the research was in progress.



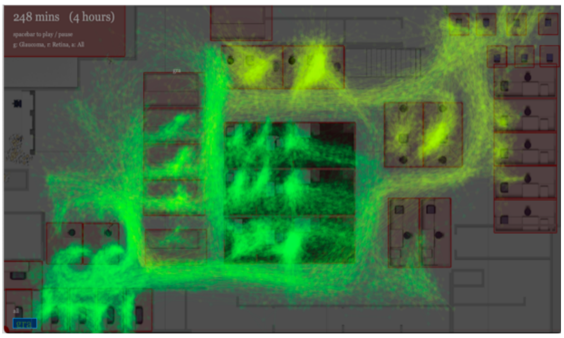


Fig. 3. Example box plot of day of week difference in phase 3 experiment.

Fig. 4. Spatio-temporal visualisation phase 3 glaucoma green, retina yellow.

Additional spatial flow visualisations (figure 4) were created to explore and identify patterns in movement around the clinic. Created in Processing (Processing, 2023) the data visualisation enabled a spatiotemporal analysis of either individual patient journeys or patterns from a group of patients (e.g. by different days of the week).

Two factors that influence CO_2 concentration are the location and density of people. The spatial distribution of CO_2 sources from people (average over periods of time – from figure 4) was determined by mapping data from figure 4 on to an unstructured 2D mesh of the clinic with a finite gaussian source (of radius 0.2 m) added at each registered location. Figure 5 shows the normalised CO_2 source distribution for the different patient class along with the same distribution for staff. The images show the relatively complex space and how the pathways for patients passing through different diagnostic channels.

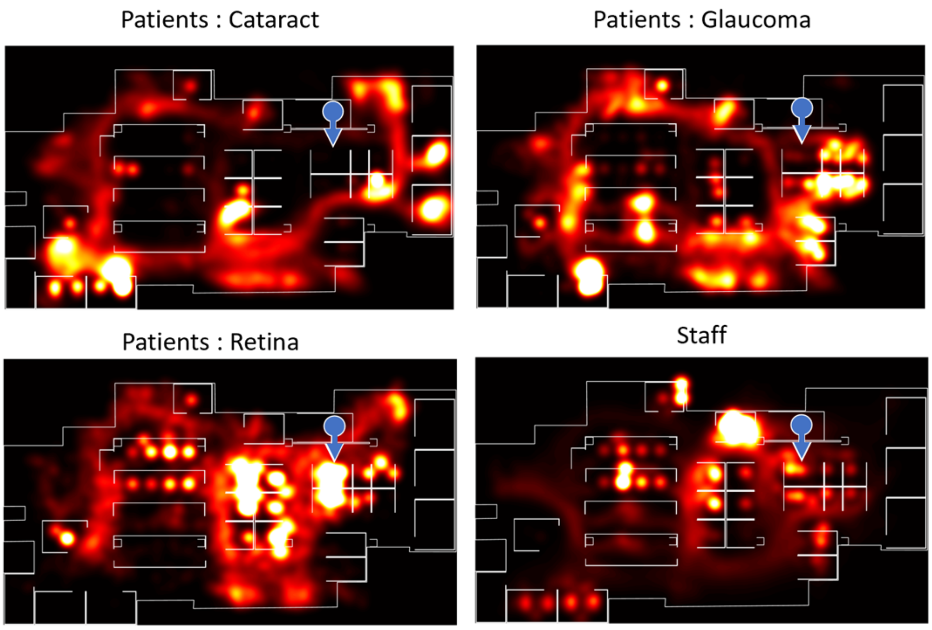


Fig. 5. Heat map showing the effective source of CO2 from patients and staff (phase 4) determined by adding a gaussian source to an unstructured mesh representation of the space. The white lines represent the vertical barriers within the space. The blue symbol shows the direction of camera used to take the photograph in figure 3.

4. Results

Analysis of the spatial flow, statistical analysis of visit times and comparison with manually observed patient journey data demonstrated the capability of the UWB sensor to track patients around the clinic. Whilst the automated data capture does not provide the same level of individual detail (i.e. why a visit length might have been longer due to a problem with the machine or an elderly patient moving more slowly through the clinic) it captures 100x more examples of total journey length to support statistical analysis.

Hypothesis 1 – patient visit time reduces as staff get familiar with new layouts. One concern with trying different layouts was that change would disrupt the technician's workflow leading to longer visit times whilst they became familiar with the environment. A linear regression was used to model the relationship between the patient visit length and time.

In phase 1 and phase 2, some reduction in patient visit length is observed (Fig. 6a slope of -0.36 and Fig. 6b slope of -1.1 respectively) and in phase 3 an increase in time can be observed (Fig. 6c slope of 0.14). During phase 4 no change in mean visit length is observed (fig. 6d slope of 0.004). This suggests that adaptation to a new environment has no significant impact on the over journey time through the clinic.

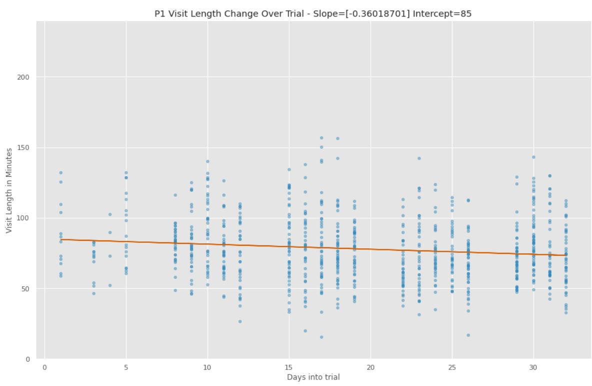


Fig. 6a P1 Visit Length over time

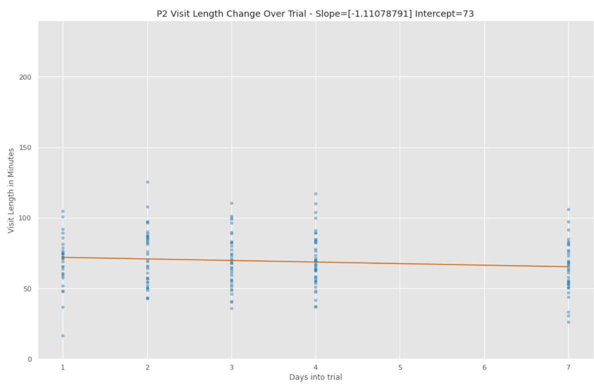


Fig. 6b P2 Visit Length over time

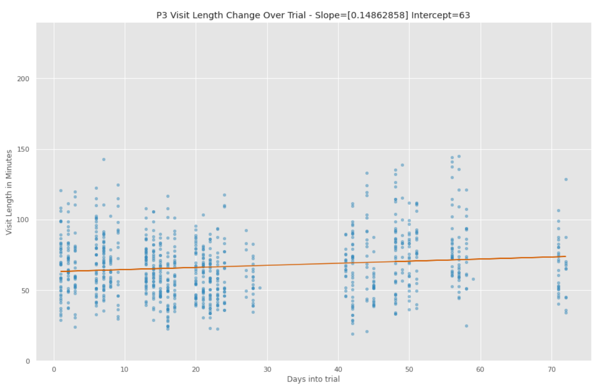


Fig. 6c P3 Visit Length over time

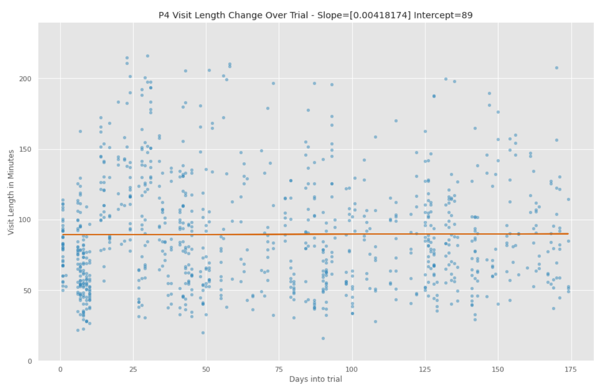


Fig. 6d P4 Visit Length over time

Hypothesis 2 – layout of the clinic influence patient visit lengths. Throughout the trial phase design meetings were held to review activity in the clinics. Phases 1 to 3 were perceived to be incremental improvements, with phase 4 introducing greater complexity to the environment, through the introduction of face-to-face pre-operative cataract surgery assessments which probably eroded some previous gains in efficiency. The mean visit times were:

P1 - 77 mins n=1028
P2 - 69 mins n=187
P3 - 68 mins n=1086
P4 - 91 mins n=924

Figure 7a-d illustrates the mean patient journey time, split by condition (Fig. 7a-c show glaucoma and medical retina, Fig. 7d shows cataract, glaucoma and medical retina), in phases 1-4 (P1, P2, P3, P4). Each y axis is normalised across the four charts to highlight the larger spread of journey times for phase 4. This data supports qualitative feedback from staff in the clinic and highlights that layout and organisation of the clinic can have an impact on patient visit times.

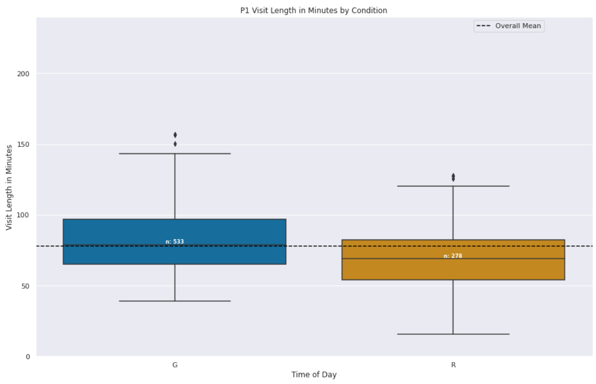


Fig. 7a P1 Visit Length by Condition

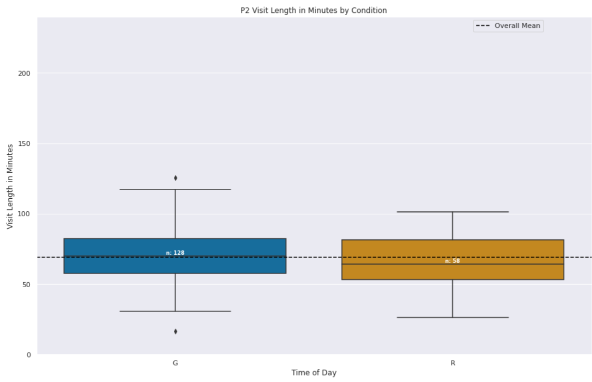


Fig. 7b P2 Visit Length by Condition

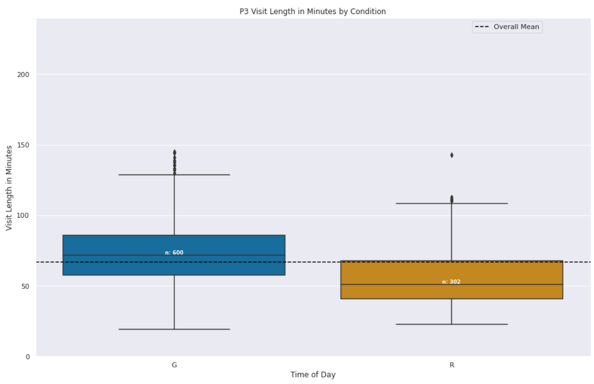


Fig. 7c P3 Visit Length by Condition

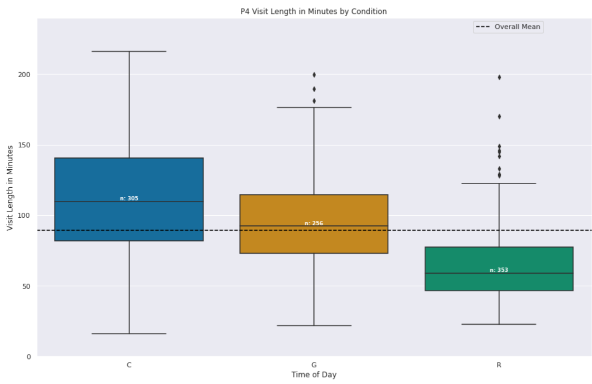


Fig. 7d P4 Visit Length by Condition

Hypothesis 3 – The CO2 concentration within the clinic - in the absence of heating and cooling - has the same trend as the number of people present. The CO_2 concentration (in the absence of heating and cooling in the ground floor) in figure 8(d), shows the same variation as the average number of people in the space (figure 8(b)). The spatial distribution of CO_2 (figure 9), shows a maximum near the stairs at 15.00. This occurs because the collective effect of people leads to heating that drives an air flow pattern to the (closed) second floor, that is then driven down the stairs, to air sampler 5, by cooler air from second floor.

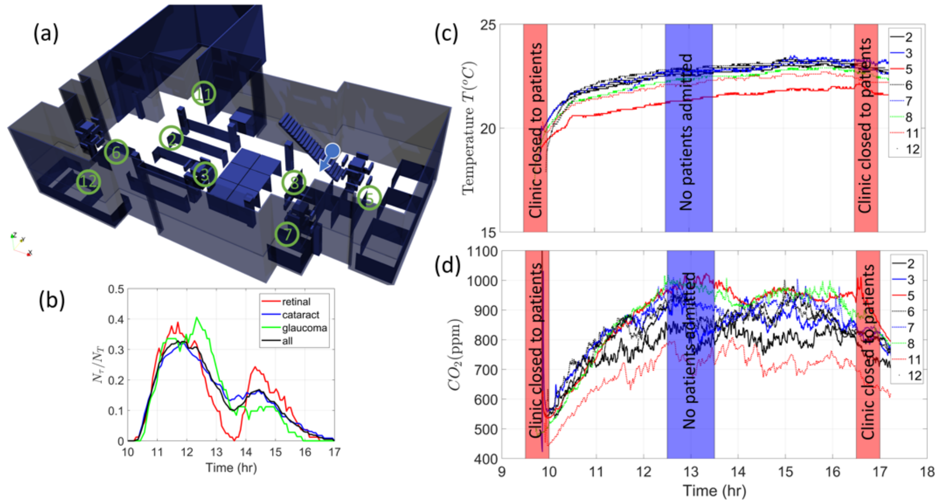


Fig. 8: (a) Three-dimensional representation of the space showing position of air samplers. (b) The number of patients over time from 10:00 to 17:00 (averaged over a number of days) and grouped into clinical pathway (retinal, cataract, glaucoma). (c,d) Variation of temperature and CO_2 concentration with time at the measurement points (indicated (a)).

This latter point highlights two primary observations from this work: we were over optimistic about the assimilation of large volumes of IoT data - bringing together data from multiple technical systems is challenging, which is compounded by the difficulty in then representing that information in a format that can be interpreted to make design decisions; secondly, the challenge of multi criteria optimization - trying to isolate root causes in human-technical systems, for example, staffing levels, are hard to isolate in complex systems such as these. Even with these challenges, IoT data has enabled enhanced understanding of patient flow and has been used as a positive input into the design of the clinic environment and continues to be used to develop best practice.

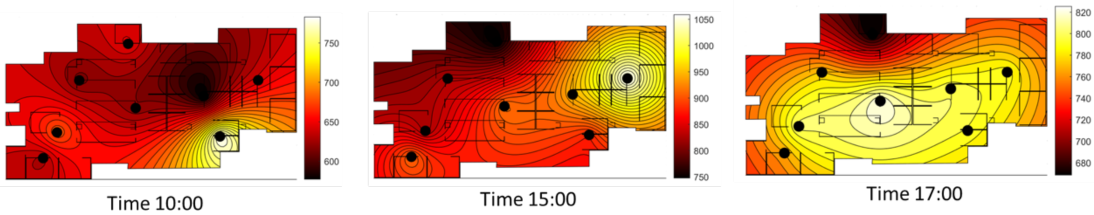


Fig. 9. Spatial distribution of CO_2 (corresponding to figure 8) at times 10:00, 15:00 and 17:00. The time of 15:00 corresponded to the maximum CO_2 concentration in the space (1050ppm).

5. Conclusions

The aim of deploying IoT technology in the clinic environment was to understand to what degree data driven insights could inform decision making. The project has highlighted areas where continuous real-time monitoring adds value above existing point in time observational analysis. Seeing longitudinal trends provided the evidence required to support design decisions.

For example, visit length does not significantly reduce over time as staff get familiar with the layout.

A secondary benefit of the data captured was the ability to visualise the flow of patients in different ways. Whilst the statistical representations helped inform macro level decision making, the spatiotemporal visualisations of flow enabled conversations with the technicians in the clinic to understand the patterns of behaviour of space usage. In the latter case observations were sometimes counter intuitive to how the space planners thought the space would be used.

The real-time monitoring of the location of people can be combined with static measurements of temperature and CO_2 to develop new insight into the relationship between clinic layout and air quality. The air quality depends on the number of people present in a room, how they are distributed within that space and the mode of air mixing. The clinical space analysed was naturally ventilated with air conditioning units providing heat and cooling. Certain aspects of the layout were found to enhance air-quality, including wide pathways extending along the length of the space. The air quality was generally very good (typically less than 250 ppm above the Brent Cross air). The highest CO_2 concentrations (>1000 ppm), located at the bottom of the stairs, was not correlated to a high local concentration of people but due to an anomalous air flow path: hot air rose to the second floor, where it mixed and was cooled by air-conditioning units, and then flowed downstairs. Our next steps are to integrate the new spatiotemporal information of patient-staff locations with a 3D computational description of air flow movements to guide an airborne risk analysis.

Whilst the majority of data analysed to date has been anonymous, future integration with patient data would support a deeper understanding of the flows through segmentation of the data by demographics such as age groups. At present these datasets are separate but discussions are underway to merge anonymised demographic data to support further analysis.

At a broader level, this research has the goal of developing our understanding of factors that influence the flow of patients through clinics to the extent that we can model how a new clinic might perform. Such simulation tools will enable the proactive design of clinics that are fit for purpose and adaptable to the constraints of their physical location.

6. Acknowledgements

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