Foundational Transdisciplinary Research Methods

Imperial College London

Dyson School of Design Engineering

Architectural Grey Space Design and Luminosity: Examining Their Effects on Foot Traffic

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Wordcount: 7990
December 13, 2024

Abstract

People's activities in urban environments are diverse and go beyond traditional functional spaces. Urban grey spaces are transitional and ambiguous, with varying impacts on human behaviour. Light, as an essential and quantifiable natural element, plays a crucial role in shaping human-environment interaction.

This paper seeks to investigate the influence of ambient light on human behaviour in grey space. It reviews the variations of natural light within a space and its effects on human's performance and emotional responses. This will help to establish an appropriate link between light and grey space to improve cognitive performance and demonstrate the interaction between architectural design and human behaviour.

This involves integration of behaviour analysis (participant route tracking) and semi-structured interviews to capture subjective experiences within grey spaces. Measuring of average natural light within grey spaces acted as quantitive basis for mathematical analysis. A hierarchical classification framework for grey space was used to model interconnected spaces at the Imperial College campus using graph theory. Several statistical measures were then in the mapping of two main correlations: (1) the foot traffic and route references that representing behaviours of students using grey areas with and without elevated grey areas when commuting; (2) the correlation between the amount of potential light that actually enters the grey space and the grey space cognitive centrality score.

The results of this study provide new insights into the design and use of grey space, specifically how exposure to light is crucial in ensuring the usage of the space and informing the architectural and behavioural psychology literature.

Keywords: *architecture, luminosity, human behaviour, preference, grey space*

Contents

Chapter 1

Introduction

> **Definition:** ***Grey space***
>
> A "grey space" is a transitional, in-between concept that refers to the space between public and private spaces.
>
> *If the space regarded as colour, indoor space as "black", outdoor space as "white", then the transition space within indoor and outdoor will be called "grey space". Grey space is the the transition space from inside to the outside of building and from private space to public space, which consisted of a series of architectural elements like garden balcony, building entrance, opening sided-courtyard and bottom overhead space.*
>
> – Gong & Hu, 2017

In the rapidly evolving urban environment, the complexity and diversity of architectural design continues to grow. Traditional urban spaces have typically been categorized simply as either indoor or outdoor, and as either public or private spaces. However, in architecture research area, a unique type of space situated between these categories has garnered attention—this is known as "grey space." Grey space exists as a transitional or ambiguous area between public, private, indoor and outdoor environments, commonly seen in modern architectural designs, such as balconies, corridors, and semi-open entrances [Tortella et al., 2021]. With grey spaces becoming increasingly prevalent in contemporary urban design, their potential influence on human's performance has emerged as an interdisciplinary topic of interest, bridging architecture and psychology. Given the strong human dependence on natural environments—particularly light—variations in natural light within grey spaces have become a critical focus of study.

With the growing interest in to incorporate grey space in the creation of sustainable buildings, there is still a gap in research on the theoretical and practical application of grey space in contemporary architecture. Empirical research can help to assess and define gray space in contemporary architecture in a more focused way. This research focuses on how luminosity in grey spaces influences foot traffic preference. The study aims to provide practical insights for architectural design, and seeks to address a gap in the current literature concerning the implications of grey spaces and luminosity.

"Foot traffic" is the primary study variable, and refers to the movement of pedestrians within a specific area. It is often used to describe the number of people passing through or utilizing a space over a given period. In the context of urban studies and architectural design, foot traffic is a critical metric because it directly impacts the usage and functionality of public spaces, such as parks, plazas, and corridors. Effective lighting enhances visibility, which can lead to increased foot traffic. Well-lit areas are perceived as safer, prompting more use, particularly in the evenings and at night [Dastgheib, 2018]. This is important in transitional spaces like grey spaces, which may otherwise be avoided due to perceived safety concerns.

By understanding and optimizing foot traffic through lighting, urban planners and architects can improve space utilization and enhance the overall functionality of grey spaces, contributing to more vibrant and safer urban environments.

1.1 Purposes, objectives and aims

1.1.1 Purposes

This study is conducted to investigate the effects of ambient light exposure on people's behaviour in grey spaces. Grey spaces have a great influence on the psychological states of individuals. By focusing on the interplay between light, space, and human behaviour, research provides insight into how such spaces can be designed to include behavioural interventions, especially for people's emotional well-being and cognitive health.

1.1.2 Objectives

1. Luminosity Mapping and Grey Space Hierarchy:
   - Produce a detailed luminosity map of the Imperial College London campus to analyse the distribution of natural light across various grey spaces.
   - Relate these luminosity patterns to the hierarchical classification of grey spaces, considering how light exposure defines their functional and psychological roles.
2. Foot Traffic Tracking and Evaluation:
   - Monitor and assess student foot traffic and route preferences within the campus, focusing on how these choices align with grey space characteristics and lighting conditions.
   - Analyse behavioural patterns to understand the relationship between natural light availability, grey space design, and students' commuting behaviours [Mostafavi et al., 2024].
3. Building Relationships:
   - Determine associations between natural light exposure, grey space hierarchies, and cognitive outcomes, particularly attention performance.
   - Quantify these relationships using data-driven methods such as graph theory and cognitive performance mapping to provide evidence-based insights for architectural design [Afifi, Krumrei-Mancuso & Trammell, 2023].

Overarching discussions consider key issues regarding grey spaces, including their transitional and hierarchical classifications, their relationship with foot traffic dynamics, and the interaction with light exposure. The aim of this study is to contribute to greater understanding of the role these factors play in shaping human behaviour and spatial experiences [Qiu & Lai, 2024].

Chapter 2

Literature Review

2.1 Grey Space Theory

The idea of grey spaces was introduced by Japanese architect Kisho Kurokawa in the 1980s, describing transitional spaces that exist as a bridge between two defined areas. [Kurokawa, 1994]. The concept of "in-between" spaces comes from the way urban planning divides areas into public and private spaces.

The concept of grey space can be traced back to ancient China, specifically the philosophies and spatial concepts of the Spring and Autumn Period and the Warring States Period (770–221 BC) [Falkenhausen & Jun, 2014]. In Western architectural traditions, the idea stems from figure–ground theory, which is one of its three main foundational theories [Trancik, 1991].

Grey space is often described using different terms to denote its ambiguous, uncertain nature, as it can not fit neatly into predefined categories or rules. An example of this ambiguity is Hüter, 1976's suggestion of a holistic approach to architecture, aiming to create a cohesive whole that seamlessly bridges internal and external environments, connecting architectural spaces with nature. Grey space also aligns with ideas of transparency within architecture, where buildings are not just physical boundaries but allow for a free flow between inside and outside [Rowe & Slutzky, 1997].

The concept of grey spaces originated from architecture and has since been applied to urban design and psychology. These spaces are characterized by their ambiguity and transitional nature, not fitting neatly into the categories of public or private spaces. For example, university campus corridors or shared walkways act as neither fully indoor nor outdoor spaces. This ambiguity allows grey spaces to offer flexible environments that enable casual interactions and activities, creating a unique and dynamic setting different from traditional indoor and outdoor spaces.

2.2 Impact of Grey Spaces on Behaviour

The core of grey space theory concerns how such ambiguous spatial boundaries influence individual behaviour and experiences. Studies have shown that grey space openness and fluidity can alleviate feelings of confinement and improve emotional well-being [Tortella et al., 2021]. However, due to the variability in their location and design, grey spaces often experience dynamic environmental factors, such as changes in lighting and ventilation, which could impact individuals' behaviour in multiple ways.

Psychological studies suggests that negative emotions, distress and anxiety decrease significantly during the transition from man-made to natural environments [Bolouki, 2023]. However, negative emotions, distress and anxiety increase significantly during the transition from natural to man-made environments .

Grey space theory, therefore, serves as a foundation for understanding how spatial characteristics and environmental conditions shape individual experiences.

2.3 Luminosity's Influence on Performance

Natural light plays a crucial role in regulating both physical and mental health. Research has shown that exposure to natural light significantly influences human's performance. The benefits of natural light extend to improving alertness and overall well-being, which highlights the importance of its inclusion in environments such as grey spaces. Humans are diurnal creatures, typically exposed to light during their daily life. These responses to light first involve subcortical structures related to alertness, such as the hypothalamus, brainstem, and thalamus. They also engage limbic regions like the amygdala and hippocampus, which then regulate activity in cortical areas, ultimately affecting behaviour. Therefore, light is a critical modulator of brain function and daily behaviour [Vandewalle, Maquet & Dijk, 2009].

Compared to artificial light, natural light is more variable and complex, which often triggers physiological responses. Within grey spaces, where the open nature leads to frequent light changes, these dynamic characteristics of natural light can create unique cognitive effects. The combination of light variability and the transitional nature of grey spaces enhances their impact on cognitive functions and mood. This complexity highlights the importance of integrating natural light into the design of grey spaces to optimize their benefits for users.

2.4 Research Gap and Opportunities

Currently, few studies have been conducted on the effects of light intensity on human behaviour within urban grey spaces. Although some studies have explored factors such as ventilation and shading within grey spaces, these studies have mainly examined physical environmental conditions rather than the effects of lighting on human beings [Zizhuo & Xin, 2023]. Existing studies have focused on these physical characteristics of grey spaces, ignoring the potential impact of natural light variations on users' psychological and behavioural responses.

In addition, existing literature typically focuses on the effects of natural light on individuals or plants separately, or compares the effects of artificial light on people in unrelated built environments [Norikane & Kurata, 2001]. No found studies have been conducted to specifically explore the effects of different lighting conditions on human cognition in architectural spaces.

Addressing this research gap, this study aims to investigate how changes in natural light within grey spaces affect human responses. This study will provide valuable insights for architectural design to develop more comprehensive optimization strategies for grey spaces, and also help people better understand and experience different urban spaces.

Chapter 3

Methodology

This study aims to map the Imperial College London campus with links to grey space hierarchy, track and evaluate foot traffic, and gauge student reception in different spaces. Given the aims, there is a need for this study to engage with both tangible and intangible concepts. To ensure fulfilment of objectives, a mixed-methods approach, combining quantitative and qualitative data is used.

This study follows an exploratory sequential design [Clark et al., 2021]. Qualitative data is gathered and then analysed to produce grounds for quantitative data collection. Then interpretation occurs. This study design differs from usual exploratory sequential designs by collecting additional supplementary data post-analysis. This data will be used to support the findings of the study and further understand outcome rationales. The inclusion of this supplement ensures data validity through triangulation. As discussed in *Bryman's Social Research Methods* [Clark et al., 2021], data triangulation is a technique used to ensure greater validity for the data collected, and is used to engage with multiple points of data generation. Triangulation is particularly effective in studying human phenomena, as observational data–such as route tracking–is paired with qualitative understanding and quantitative analysis. This design was chosen due to the inductive nature of this study.

Qualitative data in the form of participant recorded route tracking and questionnaire results is used to define key locations of importance. Quantitative data collection in the form of light scoring in collected based on those outcomes. From here, a series of base hypothesis were created and analysed mathematically, to pin point connections between foot traffic and grey scale hierarchies. Findings from this method was directly informative of the supplementary qualitative data collection of semi-structured interviews. The data collected in the semi-structured interviews is supplementary of the typical exploratory sequential design, and was

The overarching study design is illustrated in Figure 3.1.

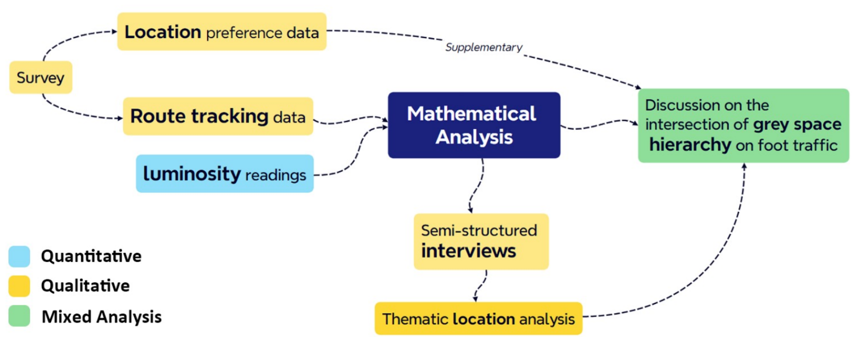


Figure 3.1: Overarching study design

3.1 Research Ethics

The ethical guideline for this study based on the framework provided in the *Declaration of Helsinki* [W. M. Association, 2013]. This framework was developed by the World Medical Association to provide an ethical framework for all research involving human participants or data.

The general principles of the *Declaration of Helsinki* places participant wellbeing as the primary concern and firmly places a duty of safeguarding on researchers. All intentions for this study were evaluated a priori to execution, and participants were given the space to communicate dissenting opinions. The study was designed to never go against the interest of the participants. Informed consent was required from participants at all stages of engagement, and steps like data anonymization was used to protect privacy and confidentiality. Local laws were obeyed and no misconduct occurred. By recruiting students a various backgrounds and experiences, under-represented groups were considered and equity was kept in mind. Due to the involvement of incentives, transparency about the requirements of participants, and the random nature of the draw was made explicit. The draw for the reward was fully random and void of researcher bias. Researchers continuously engaged in active risk assessment to avoid ethical uncertainty. Because of the generality of the target participant demographic, vulnerable populations are not impacted and no special precautions needed be taken. Additionally, this study is non invasive and does not require laborious efforts by partakers.

All study methods were approved by The Imperial College London Ethics Board (Appendix 7.3).

3.2 Survey

3.2.1 Method Selection

Surveying was selected to be the first point of data collection, and was constructed to gather qualitative data from a wide variety of participants. Survey is the optimal research method to choose because it will allow for the collection of data from a large and diverse sample, quickly. Surveying adds a great breadth of data, which improves the validity of further analysis [Creswell & Creswell, 2023]. Surveying in this case gathered various routes and paths taken by a large amount of participants, and their opinions on optimal spaces.

3.2.2 Implementation

Participants (n=20) for the survey were primarily recruited using personal contacts. All were students at Imperial College London. Posters (Appendix 8.2) were posted around Imperial College London's South Kensington campus to garner more engagement. A goal of 30 participants was determined in priori analysis to reach data saturation, however supplemental qualitative methods allow for data saturation to still be neared.

Participants were supplied with a Notion webpage link with a brief explanation on the study (Appendix 7.6), a consent and privacy form (Appendix 7.5), and a series of steps to follow. Before starting participants must acknowledge that they have read and understood the privacy and consent form. Respondents then kept track of their path around campus over the course of a day. At the end of they day, participants completed a map-drawing activity hosted on *PollUnit.com* (Appendix 7.1). Next, the participants answered a questionnaire. The questionnaire consisted of 11 questions (Appendix 7.7), as this study initially contained a broader scope of research. Questions were developed to examine preference in relation to the subjects, so centred around preferred study spaces in order to gather relevant data to this sample. Because of the multi-step nature of this study, participants were incentivised with a draw for a chance to win a £100 Amazon gift card. The gift card was given away to a participant chosen through a randomization website, *random-ize.com*

The survey is inspired by the DSM-5 [A. P. Association, 2022] to focus on the participant's feelings and emotions deeply and gather a comprehensive view of the participant's beliefs.

3.2.3 Challenges

One of the key challenges of the survey structure was participant recruitment. Given that the study had two separate steps, there was massive difference in the amount of participants that follow through as opposed to similar peer studies that consist of a single step. One of the ways this hurdle was tackled was through incentives but given the time gap needed between the study steps, this proven somewhat ineffective. Additionally, PollUnit surveys only last 30 days, so there was a time crunch for data collection.

3.3 Light Scoring Method

3.3.1 Method Selection

Luminosity is a key element of this study, it was important to gather accurate and hard data for valid analysis. Based on initial definitions of grey space, hierarchy spaces were selected to represent different levels. The data gathered in the route tracking part of the survey further identified key locations around campus. Qualitative data and literature defined the decision to examine 40 locations on campus. Measuring light that is not produced by the researcher is difficult, as the power of light sources is unknown. The most assured way for accuracy is to measure light at the point of contact where subjects would experience the luminosity. This was measured in units of LUX, or lumen per square meter [Tabaka & Wtorkiewicz, 2022], by use of a light meter. By using this data a luminosity map of campus was created, from which individual scores were collated for each grey space.

3.3.2 Implementation

To accurately map the cross campus lighting, a scoring tool was used and readings were taken across different times. A Digital Illuminance Light Meter (Appendix 7.8) was purchased and taken to 40 different locations on the Imperial College London campus. This light meter reads up to 200,000 LUX. These locations were chosen to give a variety of lighting conditions, catch anomalies and read all the major walking routes that students are known to take. All locations were visited over two sessions. One session took place later in a cloudy day, and one earlier in a sunny day. This gave the opportunity to find low and high readings for each location. Pin pointing the two ends of the spectrum then allows for easy regulation of the scores, as a median number was produced for each location.

3.3.3 Challenges

Light scoring presented some key challenges in the data collection as months, days, hours, and even minutes can fundamentally change this data. To ensure measurement validity, an offset approach was taken to collection. Offsetting the strengths of a high-illuminance day with a low-illuminance day is important to regulate the data from each set's weaknesses. In future iterations of this study more data sets would be important to collect. Collecting this data form for all times of day, different weather conditions and different times of year would strengthen the data-weakness offset and contribute to data completeness.

3.4 Mathematical Analysis Methods

3.4.1 Method Selections

Once the data has been collected, providing a basis for quantitative comparison can be achieved with the implementation of mathematical structures that can model the relationships between variables. The use of weighted graphs offer a way to provide both visual and mathematical analysis on grey space structures and the interactions between them. Graphs networks are frequently utilised in sociology studies in order to model social networks and crucially, the dynamic nature of interactions (edges) between people (nodes) [Evans & Lambiotte, 2010; Toivonen et al., 2007]. One key way of analysing graphs are centrality measures. Centrality is crucial to understand the underlying phenomena of the effect of nodes in a graph network [Landherr, Friedl & Heidemann, 2010]. There are many different centrality measures designed to each address a particular question about the network and depending on what measure is used, it can detail what nodes in the graph are of particular importance in whichever respect is required. One centrality measure is degree centrality, which counts the number of connections the nodes has to other nodes. Centrality was first thought of a way of measuring the most important nodes in communication networks but was quickly adapted for sociological networks. Freeman, Borgatti & White, 1991 displayed the use of betweenness centrality for a flow graph (a weighted directional graph), from which certain novel principles can be used for the analysis of grey space structures as a graph network.

3.4.2 Overall Implementation

To first build a graph network of grey spaces, a hierarchy of grey space levels is uniquely devised for the case presented. As indicated from the name, grey spaces are transitional and theoretically vague, being the bridge from the inside to the out [Sheng et al., 2018]. Qiu & Lai, 2024 is one of the first works to formalise levels to these gray spaces, introducing a hierarchy as grey spaces transition from inside (black spaces) to outside (white spaces), with the idea being that more spacious grey spaces that are designed to have a higher foot traffic would theoretically be higher in the hierarchy. Additionally, she displays this hierarchy as a graph network but for visualisation reasons. By adapting her hierarchical methodology to the grey spaces of the Imperial College campus, her grey space graph visualisation can be built on by using centrality to provide an ample basis for visual comparison.

Grey spaces are separated into three different hierarchies as so:

Level 3: The bottom layer in level of grey space, encompassing walkways and corridors that classrooms (black space) immediately feed into.

Level 2: The middle level of grey space used to describe major walkways and most department buildings foyers.

Level 1: The highest level of grey space. These include major internal streets and plazas within campus.

Level 0: White space - officially outdoors. This is included for contextual reasons; it is hypothesised that white space around campus is used to for inter-campus travel due to the preference for pedestrians for prevalent light exposure [Ferrer, Ruiz & Mars, 2015].

The data collected from the survey about walking paths is collated to provide a weight to each edge in the campus graph network. Degree centrality is used to assign a level of usage to each node, denoted as foot traffic. Using several statistical metrics allows there to be seen if there is a correlation between foot traffic and the hierarchical level of the grey space. It is expected that there will be a negative correlation, since this is in-line with the given definitions of hierarchy. This relationship is then further explored, comparing whether the light data has any effect on the foot traffic on grey spaces. Finally, betweenness centrality is used on the graph to determine if foot traffic follows the shortest path.

3.4.3 Grey Space Hierarchy vs Foot Traffic

As background information about the nature of the relationship between grey space hierarchy and foot traffic is limited, a range of statistical tests were used in order to ascertain this nature, each using a different set of assumptions. Linear regression (Pearson's), the simplest, is utilised as a comparison tool and makes the most assumptions about the data such as linearity between the two variables and normality in the difference between predictions and observations. Treating the grey space hierarchical ranking as continuous allows for the modelling relationships in an interpretable and computationally simple way [Kumari & Yadav, 2018].

The Intraclass and Spearman's correlation coefficient statistical tests are more suited to understand the relationship between hierarchy and foot traffic. The Intraclass is a statistical method that assesses agreement or consistency within groups based on classes while the Spearman's Correlation is used to quantify not just the strength but direction of an association as well (if it is positively or negatively correlated). Key to the analysis of results, Spearman's is a non-parametric measure so it does not assume normality while the other two tests do. In addition, Spearman's can be utilised with uneven data structures in contrast to Intraclass. As a result, Intraclass classes with smaller numbers of elements, such as white space, are oversampled; randomly repeating sample points until the number of elements in the class is the same for the largest class set (in this case, Grey Space Level 2) [Vandewiele et al., 2021].

3.4.4 Foot Traffic vs Luminosity Score

As mentioned earlier, a relation between the exposure of a node in our graph to light and the amount of foot traffic it receives is hypothesised as a positive correlation. But yet again, there is limited background information on the population nature of the variables. As a result, three statistical correlations are used to in order investigate this relationship, yet again, in order to build a better profile of correlation using the range of assumptions under which each statistical test is built on.

Linear regression is more suited to two continuous variables as opposed to the ranking and continuous variable pair in the previous comparison. As such, it's data can be better interpreted to indicate the relationship. But yet again, as normality of the population can not be guaranteed, Spearman's non-parametric nature is also useful in the investigation. In addition to testing for a linear relationship, a 2nd order polynomial regression is applied to the data to determine a coefficient of determination (R-squared) and if the variables do display a non-linear relationship [Ostertagová, 2012].

3.4.5 Visual Graph Analysis

In addition to mathematical analysis, visual analysis is an effective tool to determine correlation. A straightforward dot plot of the independent variable over the dependant may lead to new insights into their relationship and crucially, give an outlook into its characteristics [Zhang et al., 2015]. However, this visualisation is limited. As such, graph networks of the grey spaces for each variable are constructed to determine particular nodes of interest that either serve to verify our hypotheses between the measured variables or to highlight discrepancies. Other methods utilise focus on overall trends, but visual graph analysis is useful in analysing a particular grey space to further explore the context behind it [Brandes & Wagner, 2004]. Sheng et al., 2018 uses graph theory for the visualisation of his hierarchy. To compound this, a useful way of determining the ideal path in a graph network is the betweenness centrality. This measure is used to assign a measure of importance to a node based how prevalently it features in the shortest path between nodes. In formal terms, betweenness of a node is defined to be the fraction of shortest paths between pairs of vertices in a network that pass through this node [Newman, 2005].

The betweenness centrality graph shows which grey spaces are the most influential for the shortest paths on campus and as such, see if this is reflected in the foot traffic graph. As betweenness centrality treats all nodes as the same and doesn't take into account the nuances of the grey spaces such as their size and time to traverse, a correlation coefficient analysis would be limited in it's usefulness. The version of the betweenness centrality that is used is Freeman, Borgatti & White, 1991's version for unweighted graphs.

3.4.6 Challenges

Key challenges of this method are primarily linked to the scope of this project. Given the short time frame of this study challenges arose, such as small sample sizes, low response rates, and the limited light sample data. Additionally, the size of the campus presents an interesting issue where there is not many examples of each class of space. For example, only three white spaces are mapped. Although this method was able to be executed, larger databases and longer time frames would add to the validity of outcome for this report.

3.5 Semi-Structured Interviews

3.5.1 Method Selection

To complement the findings from the traditional exploratory sequential study structure, semi-structured interviews were introduced. This qualitative gathering adds depth, and helps to pin-point rationales in order draw meaningful conclusions. Semi-structured interviews allow interviewers to adapt to respondents [Clark et al., 2021].

3.5.2 Implementation

Participants were recruited from personal contacts. Participants were required to provide informed consent (Appendix 7.5). Six participants (n=6) were taken to three locations across the Imperial College London campus and asked five questions. (Appendix 7.4) The three locations chosen were the Dyson School of Design Engineering foyer, the Abdus Salam Library walkway, and the foyer of the Electrical and Electronic Engineering building(EEE). These were chosen after a mathematical analysis was completed, which spotlighted these locations as level 2 grey spaces that do not feature as walkways on our graph and feed into level 1 grey spaces. These are examples to see what the limitations of our variables prevent us from understanding about grey spaces. The questions probed participants about their relationship to the space. Interviews were audio recorded, and transcribed. Recordings and transcriptions were stored in offline drives and deleted after transcription, to preserve participant privacy. Transcriptions were uploaded to NVivo, a tool for transcription and thematic analysis. NVivo allows for coding and deep thematic analysis, to garner insights and overall sentiments Maher et al., 2018. Thematic analysis proceeded for each space separately.

3.5.3 Challenges

There were limited challenges in this method, as personal contacts proved willing to answer questions without issue. The limited scope of this study proves a challenge as small sample sizes do not ensure data saturation occurs, and could make data unreliable. Given that method acts supplementary to the main qualitative and quantitative methods, there is little disruption on the results.

Chapter 4

Results

4.1 Survey Results

4.1.1 Demographic Results

Respondents answered three demographically related questions to understand student relationships to campus, and ensure a wide variety of students were engaged. Out of the 20 participants, 11 identified as male, 8 as female, and 1 as other. 7 participants fell between the 18-21 range, 10 between 22-25, 2 between 25-29, and 1 self identified as between the ages of 30-40. Postgraduate taught students represented half of respondents. One represented each postgraduate research, PhD, and undergraduate year 4+. Two students represented each undergraduate year 1, 2, and 3.

4.1.2 Route Tracking Results

All respondents provided informed consent and agreed that they had read the privacy and consent form [Appendix 7.5]. The results from the PollUnit survey, show a wide variety of routes taken through each student's day, as shown in 4.1. These routes were kept for further analysis in the quantitative method.

Figure 4.1: Raw data gathered from student route tracking self-report section of the survey method.

4.1.3 Questionnaire Results

Respondents were asked "*What environment do you feel the most productive in?*", of which all 20 answered. 7 answers noted silence as key, and 2 mentioned good lighting as important. 6 answered that the library is their most productive environment, and 4 mentioned their own private homes or labs. Relevant answers included; *"Bright light, minimal sound, good table*", *"Anywhere that has good natural light, or scenery of nature"* and *"Lighting is a huge factor, lighting that is too cool toned and office-like, makes focus more difficult and strain the eyes quickly*".

When asked "*Out of all the places you visited today, where would you like to study the most?*," 16 out of 20 respondents gave on-campus responses. 10 answered that the main Abdus Salam library was ideal, 2 answered that the City and Guilds building was ideal, and one answered the EEE building. One respondent answered the Sherfield building crediting the natural lighting.

4.2 Light Scoring Results

Light scoring results, were obtained for all 40 locations on campus. The light scores ranged greatly from 11-2589 LUX. These scores were cross-analysed with the route tracking inputs from the survey methods to produce data for the first stage analytical method.

4.3 Quantitive Analysis Results

In the absence of relevant data about population parameters to derive a natural hypothesis test, two methods of creating a population are used to derive confidence intervals from; bootstrapping and permutation. Confidence intervals are used to allow for inference to be drawn from the data by seeing how close the value is to the 95% threshold typically devised [Hazra, 2017]. Both techniques involve random resampling of the observed data to create a population from, with slight difference to to the calculation of this population. Correlation coefficients classifications offer more insight into the relationship in this case due to the aforementioned limited background information but confidence intervals nevertheless help us to validate the results.

Correlation Coefficient	**Interpretation**
0.00 – 0.10	Very weak correlation (can be neglected)
0.10 – 0.39	Weak correlation
0.40 – 0.69	Medium correlation
0.70 – 0.89	Strong correlation
0.90 – 1.00	Highly strong correlation

Figure 4.2: Schober, Boer & Schwarte, 2018's classification of correlation coefficients.

4.3.1 Foot Traffic vs Grey Space Hierarchy

As seen in 4.1, the linear regression has the best correlation, indicating that there may be a linear and therefore, a hierarchical relationship. The more advanced statistical tests give much lower correlative coefficients. By using Schober, Boer & Schwarte, 2018's classification of correlation coefficients, it shows that there is moderate correlation for the linear regression, and weak correlation for the other two metrics.

In this case, both advanced statistical methods fall into the confidence intervals comfortably, supporting the null hypothesis made earlier. It is crucial to note that as mentioned previously, Intraclass only gives the level of association, not the nature of it. As such, it is only measured between 0 & 1, unlike the other two, which measure between -1 (negative correlation) and 1 (positive correlation).

Full Dataset	Linear Regression	Intraclass	Spearman's Rank
Correlation Coefficient:	-0.51	0.36	-0.37
Confidence Intervals - 95% (Method):		0.07, 0.54 (Bootstrap)	-0.59, 0.58 (Permutation Test)
Removing White Space			
Correlation Coefficient:	-0.42	0.42	-0.14
Confidence Intervals - 95% (Method):		0.07, 0.45 (Bootstrap)	-0.65, 0.64 (Permutation Test)
Removing White Space - Removing outliers			
Correlation Coefficient:	-0.56	0.89	-0.22
Confidence Intervals - 95% (Method):		0.07, 0.88 (Bootstrap)	-0.66, 0.66 (Permutation Test)

Table 4.1: A table of the correlation coefficients and confidence intervals of different datasets for foot traffic versus grey space hierarchy

4.3.2 Foot Traffic vs Luminosity Score

Full Dataset	Linear Regression	Spearman's Rank	Polynomial Regression (2nd Order)
Correlation/Determination Coefficient:	0.50	0.58	0.31
Confidence Intervals - 95% (Method):		-0.57, 0.57 (Permutation Test)	
Removing White Space			
Correlation/Determination Coefficient:	0.51	0.46	0.26
Confidence Intervals - 95% (Method):		-0.61, 0.62 (Permutation Test)	
Removing White Space - Removing outliers			
Correlation/Determination Coefficient:	0.79	0.78	0.63
Confidence Intervals - 95% (Method):		-0.68, 0.69 (Permutation Test)	

Table 4.2: A table of the correlation coefficients and confidence intervals of different datasets for foot traffic versus luminosity scores of different grey spaces

The correlation coefficients from both Linear Regression (0.50) and Spearman's Rank (0.58) in Table 4.2 suggest a medium correlation between foot traffic and luminosity scores. This indicates that there is a meaningful, though not exceptionally strong, relationship. The 2nd order Polynomial Regression has a lower determination coefficient (0.31), pointing to a weaker fit when a polynomial regression is applied. The regression captured by the polynomial model is less robust than the linear and methods for the dataset as a whole.

Removing the white space classified data, the correlations do not deviate in a significant manner. While Linear Regression shows a small improvement in the correlation coefficient (0.51), Spearman's decreases (0.46). Nevertheless, this still falls within the medium correlation range. This implies that Spearman's is more sensitive to the white space portion of the data, which features some of the highest luminosity scores. The polynomial determination coefficient drops further (0.26), reflecting a weaker non-linear relationship.

The most substantial change occurs when both white space and luminosity outliers are removed. Linear Regression and Spearman's in this case rise dramatically (0.79 and 0.78 respectively), indicating a strong correlation according to the classification in Table 4.2. This highlights that outliers and extraneous data were heavily dampening the regression in the earlier analyses. The determination coefficient for Polynomial Regression also improves significantly (0.63) but not as strong as the linear models, further demonstrating a reduction of noise in the refined dataset.

4.3.3 Visual Analysis

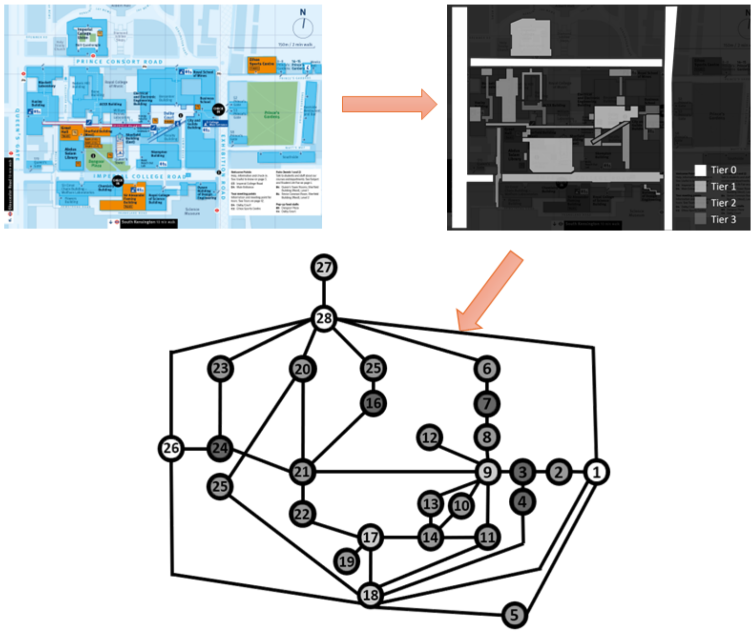


Figure 4.3: A visualisation of how grey space hierarchy was applied to campus and turned into a graph

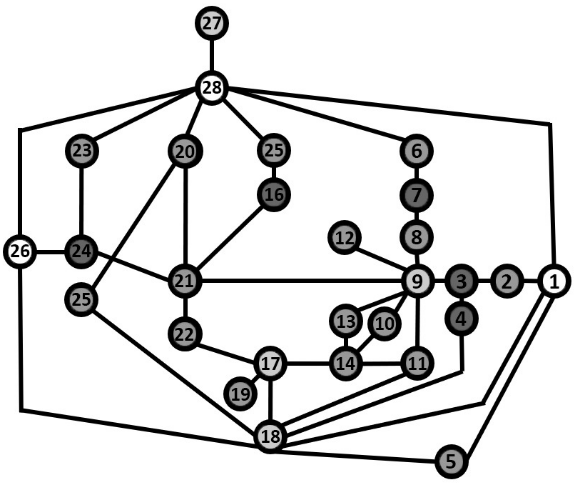


Figure 4.4: The grey space network graph using a colour map to signify grey space hierarchy

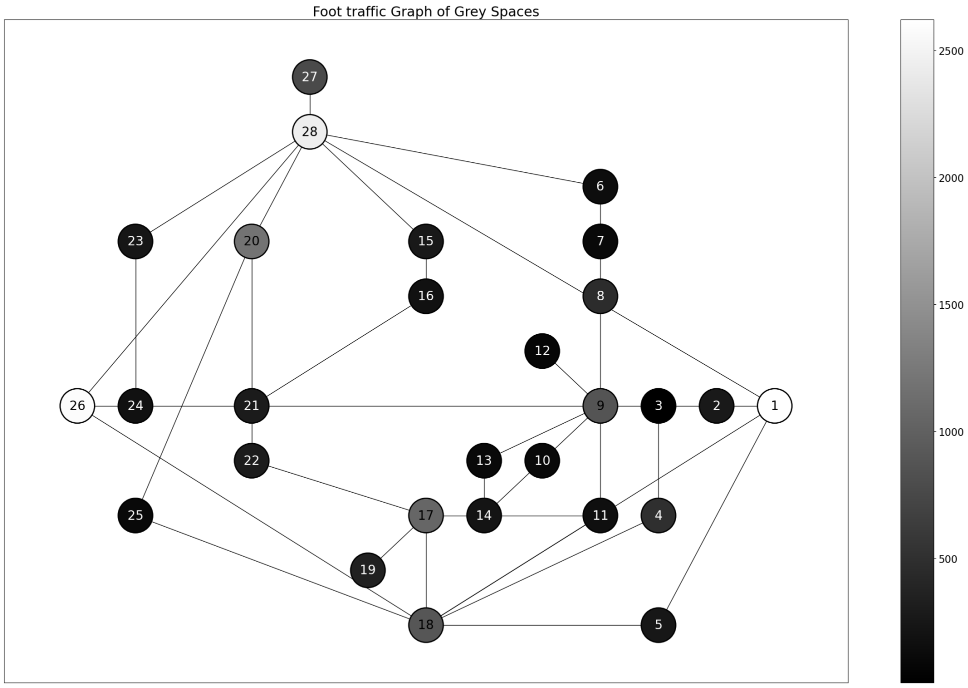


Figure 4.5: The grey space network graph using a colour-map to signify foot traffic

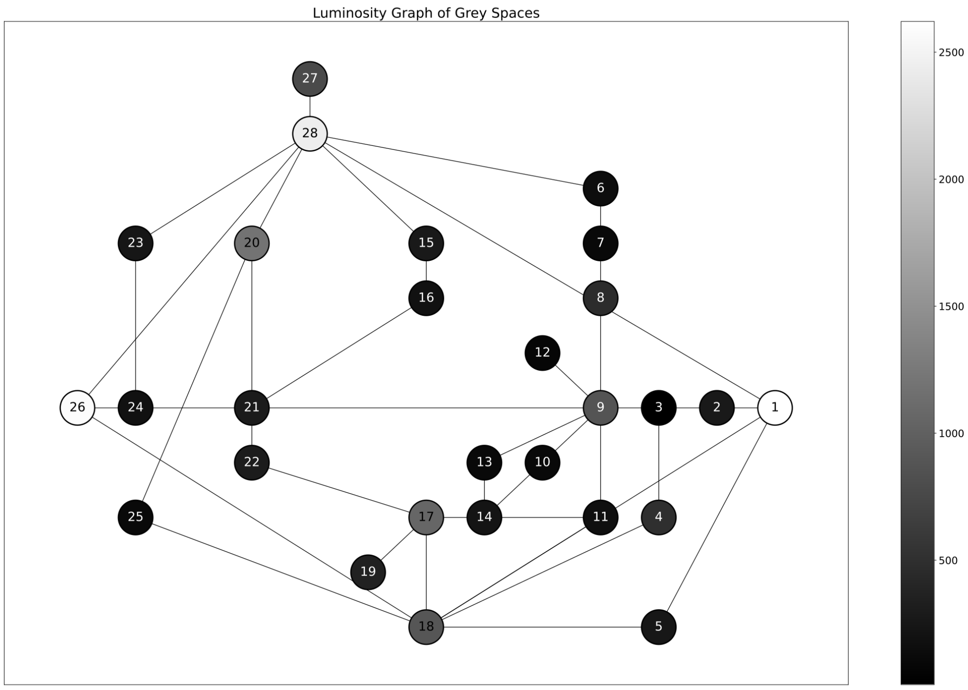


Figure 4.6: The grey space network graph using a colour-map to signify luminosity

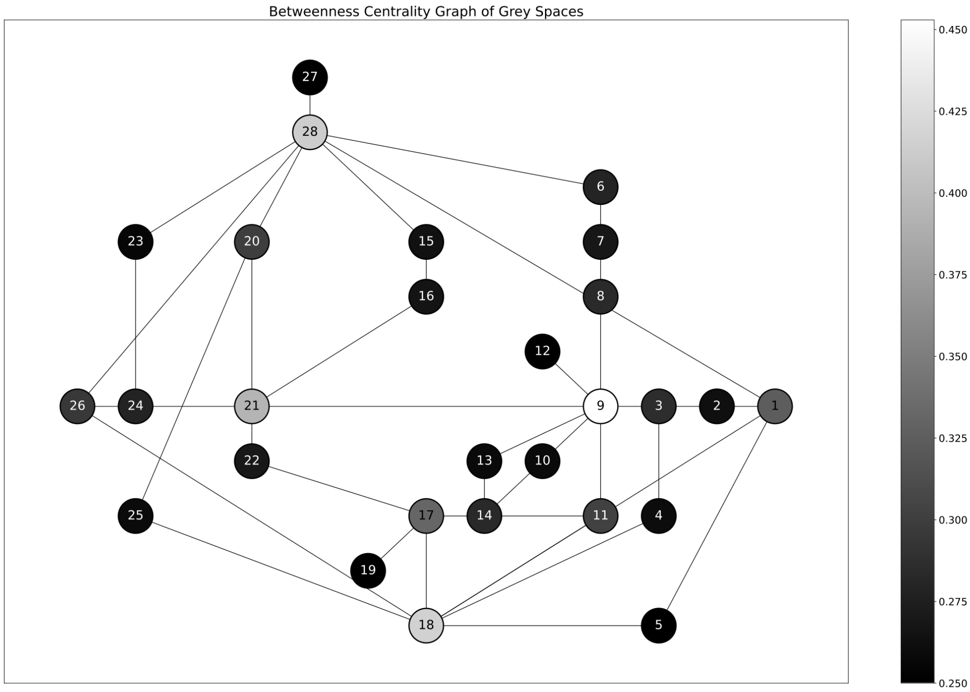


Figure 4.7: The grey space network graph using a colour-map to signify betweenness centrality

The variables explored thus far are visualised using the graph mapping of campus and are then colour-mapped based on their values. This is in addition to the betweenness centrality, which shows the nodes that most frequently make up the shortest distances on campus.

Comparing all the graphs (Figures 4.7, 4.6, 4.5, 4.4 for betweenness, luminosity, foot traffic and grey space hierarchy respectively), a few notable key grey space nodes can be seen.

When observing the white spaces (1,26 and 28), an interesting trend can be observed. Most have high scores in all metrics except betweenness. 1 and 26 are not often on the shortest paths according to the betweenness centrality but are often used nevertheless to navigate to another area of the college. 28 is different in that it score highly in the respective metric as well, thereby conforming to the trends expected.

Level 2 and 3 grey spaces mostly conform to the trends; their low centrality scores, hierarchical status and luminosity is reflected in their lack of foot traffic. Two notable examples are the pairs 20 and 21. 21 has a highest betweenness centrality score out of all. However, it still has low foot traffic numbers despite being a crossover path for many of the supposed shortest routes through campus. This is contrast to 20. This node has a lower centrality score but is better illuminated. As well as this, it features unusually high foot traffic and much higher than its neighbour.

Finally, level 1 spaces are for the most part, consistent with each other. They feature most of the highest foot traffic, luminosity scores and betweenness centrality scores of the grey spaces. They slightly differ on their betweenness centrality scores, with 9 being very high overall, but this is not reflected in any other metric.

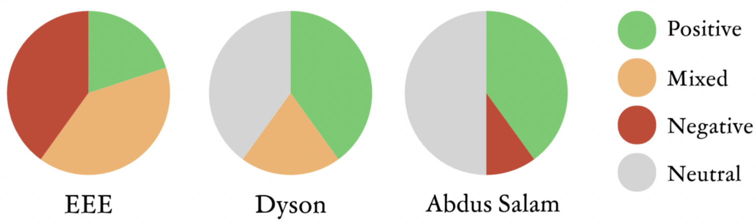


Figure 4.8: Figure 4.4: Sentiments derived about spaces on the Imperial College London campus, obtained by semi-structured interview analysis.

4.4 Semi-Structured Interview Results

After transcription, coding and thematic analysis revealed results for each space visited. Sets of interviews were combined and sentiment visualizations were extracted. All participants provided informed consent prior to interview. The EEE building was received most negatively by participants, with 80% of transcription reading as non-positive —half being negative. The library walkway was rated second lowest with interviewees' sentiments read as half neutral, and 10% negative. The most positively rated space was the Dyson School foyer, which read with no direct negative sentiments. Key reasons cited for the negative EEE reception was dark lighting. This contrast the library walkway and the Dyson foyer which both garnered positive reviews relating to the accessibility of light, and overall space luminosity.

4.4.1 The EEE Building Foyer

Overall sentiment for the EEE building foyer was varied, with transcripts reading approximately 40% negative in intonation, 40% mixed, and 20% positive. The interviewees noted that lighting was lacking with 2/3rd of participants suggesting improved lighting measures. Additional comments included the removal of pillars and wood panelling to improve the space. All interviewees made commentary about how the space was dark.

4.4.2 The Dyson School of Design Engineering Foyer

The Dyson foyer generated 40% positive sentiment on the recorded transcriptions, and 40% neutral. 20% of reviews were mixed. Positives discussed in this space all involved the large amount of available light, and many discussed the white paint colour. Mixed sentiment comes from a suggestion by interviewees to add more colour, or visual interest.

4.4.3 The Abdus Salam Library Walkway

The library walkway generated mixed reviews, with half of transcription being coded as neutral. Approximately 40% of the interview conveyed positive sentiment, and 10% as negative (Figure 4.4). The primary concern for participants was the crowding that occurs in this space, with all interviewees noting how busy the walkway is. Positives were noted in the large amounts of glass and windows, with all participants making comments on the lighting as a positive. Other positives mentioned include the wood panelling in the space.

Chapter 5

Discussion

This study develops aims to understand how the architectural features of grey spaces can influence human behaviour. The results generated show that there is only a moderate relationship between foot traffic and grey space hierarchy. However, the relationship between foot traffic and luminosity is stronger. These findings support the objectives of this study, and suggest that well-lit grey spaces are likely to attract higher pedestrian traffic. The complexity of human behaviour in urban spaces is highlighted in this report, necessitating a nuanced approach to understanding space usage.

Review of Objectives

The primary objectives of this study were to:

1. **Map the luminosity of grey spaces** on the Imperial College London campus and assess its relationship with foot traffic and grey space hierarchy.

2. **Evaluate student preferences** regarding space usage and emotional responses to different grey spaces, particularly in relation to light.

3. **Analyze the correlation between foot traffic, grey space hierarchy, and luminosity** to establish the impact of light on student behaviour and spatial choices.

The correlational analysis for the foot traffic versus hierarchy data more or less followed a negative medium correlation, as expected. Aforementioned, these different grey spaces hierarchies are made with the goal of handling different foot traffic loads; as the grey space goes up the hierarchy, an increase in foot traffic is generally seen. Rather surprisingly, Spearman's rank coefficient was lower on average compared to even linear regression, which was hypothesised to be the lowest. However, the most meaningful score was the IntraClass, which is a method specifically designed for ranking systems like the hierarchy. While the lower scores for the initial cases were indicative of a weak to medium correlation, the last case successfully demonstrated a strong correlation in the dataset between the variables. This conclusion is derived using Schober, Boer & Schwarte, 2018's classification, which is one of two methods of inferring from the data.

The other are confidence intervals which are derived through bootstrapping and permutation methods. These are useful for validating results in the absence of detailed population parameters. These confidence intervals show how the data is correlated in relation to the pseudo-population data generated by the resampling methods. Crucially, they allow us to infer additional information about the data and contrast it with our inference from the correlation classification. For example, all the other results fell within these confidence intervals, despite showing a more or less negative correlation across the board, denoting that these results are in line with our statistical null hypothesis of no relation. Meanwhile it also compounds the classification such as in the case of the strong correlation coefficient in the Intraclass section when outliers and the white spaces were removed, where, only just, it falls outside the confidence interval, allowing a suggestion of evidence to reject the null hypothesis of no correlation.

In contrast to the varying results of the grey space hierarchy, the luminosity versus the foot traffic gave a much more definitive result in both inference methods. Unlike in the previous comparison, all three metrics were equally viable and so all are given equal weight in their interpretation. The Polynomial regression routinely had the lowest scores, particularly in relation to the linear regression and as such, this dataset is unlikely to follow a 2nd order polynomial curve. Due to the small size of the data, using any higher order of polynomial regression may be subject to over fitting. Removing White space alone from the data was not sufficient and actually harmed the strength of the correlation in two of the metrics. However the Full dataset yielded medium correlations for the Linear regression and Spearman's but crucially also gave Spearman's coefficient as falling outside of the confidence intervals, meaning that there is evidence that even with the noise of the full dataset, there is sufficient evidence to reject the null of no correlation. For the refined dataset with no white space or outliers, there is strong evidence all around of a positive correlation, both from the classification of coefficients and from the confidence intervals.

This result lends evidence to suggest that the designed hierarchy of a grey space has less of an effect on the number of people walking through it than the amount of light available in that space. Ferrer, Ruiz & Mars, 2015 justifies the presence of white space in this data selection—despite not being a technical grey space—due to the hypothesis that it is nevertheless used by people on campus in place of existing grey space due to it's significant light exposure. Using this logic, one can infer that an inter-campus commuter is more likely to go down a path maximising their light exposure than to go through their logical by design path through a grey space hierarchy. Going off this inference, visual analysis on specific nodes determined that even the supposed shortest paths—calculated using the betweenness centrality—were not preferable to a node that was exposed to significant amounts of light. In relation to the white space hypothesis, there is further evidential support from the visual analysis. Despite their generally low centrality scores, these white spaces are the most used on campus as well as the most well lit. They are also the highest of the hierarchy, which means a direct inference is not possible in this case. However, nodes 20 and 21 are part of the same hierarchy. It is seen that 21 being the most influential in shortest paths on campus, 20 has considerably better exposure to light and indeed, as suggest from previous trends, has noticeably higher foot traffic, again suggesting that light is the notable variable in this analysis of foot traffic. Visual analysis on Level 1 nodes also gives reason to suggest that the betweenness centrality seems to have little affect on foot traffic through nodes. Despite the betweenness measures all being different for these nodes, the other variables were similar and showed no deviation indicating that people do not use the hypothetical shortest path to their destination as a deciding factor.

To further compound our inferences, the qualitative results derived give us clear insight into human preference. Semi-structured interviews provided valuable qualitative insights into students' perceptions of different grey spaces. The EEE building foyer received the most negative feedback, with 40% of participants expressing dissatisfaction. This was noted as primarily due to the lack of adequate lighting. This data supplements the quantitative method, as the EEE foyer is a space with lower luminosity scores and poor lighting conditions. Conversely, the Dyson School of Design Engineering foyer, with its abundant natural light, received predominantly positive feedback, reinforcing the significance of lighting in student preferences for study spaces.

The results indicate that both grey space hierarchy and luminosity influence foot traffic, but neither influence is fully linear or straightforward. The moderate correlation between foot traffic and luminosity—particularly when outliers are excluded—suggests that students are more likely to use spaces with higher natural light; however, this relationship is also shaped by other factors, such as space design and location. Similarly, while foot traffic has stronger alignment with central grey spaces, weaker correlations indicate that hierarchy alone does not completely explain space usage.

The ambiguous and dynamic nature of grey spaces help to decode these findings. According to Qiu & Lai, 2024, grey spaces are neither fully public nor private, nor entirely indoor or outdoor, giving them a unique psychological impact. The fluctuating luminosity in these spaces likely enhances their appeal and usability, as individuals generally prefer environments with higher natural light for cognitive tasks (Vandewalle, 2009). However, the lower correlations from advanced methods suggest that other factors play a role in determining the extent to which these spaces are utilized.

The findings of this study have practical implications for architectural and urban design, particularly in educational and public spaces. The positive correlation between luminosity and foot traffic highlights the importance of integrating natural light into grey space designs to enhance their attractiveness and functionality. Additionally, the moderate relationship between foot traffic and grey space hierarchy emphasizes the need for accessible and central spaces that foster social interaction and engagement.

This study format may be applicable to other urban settings with similar spatial characteristics,. The relatively small sample size and focus on a single campus could limit the generalizability of this study, which must be investigated in future research. Future research could include a broader range of campuses or urban spaces to determine if these findings hold across different contexts.

Researchers approached this study with awareness that biases may influence the results, and exercised precautionary measures to maintain impartiality. The researchers acknowledge that there is possibility that perspectives and potential biases may have influenced the interpretation of data, despite precautionary measures. The use of data triangulation helped mitigate these biases and enhance the reliability of the findings.

Ethical considerations were integral to the study design. All participants provided informed consent, and data anonymization techniques were utilized to protect privacy and confidentiality. The study adhered to the Declaration of Helsinki [W. M. Association, 2013] for participant protection. The researchers also ensured that no vulnerable populations were impacted and that transparency was maintained throughout the recruitment and data collection process.

Chapter 6

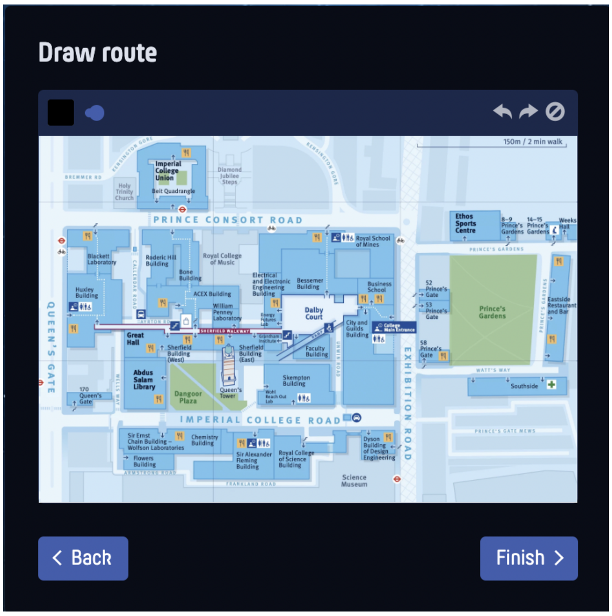
Conclusion

Overall, this study provided valuable insights into how the hierarchy of grey spaces as well as the lighting conditions influences foot traffic levels in an urban campus setting. The mathematical analysis led to a clear correlation being observed between foot traffic counts and luminosity scores. This was followed by qualitative analysis offering further insights into grey space design and how best to incorporate light exposure to various hierarchical levels of grey space in order to better reflect the tendencies of those that walk inter-campus.

Chapter 7

Appendix

7.1 Foot Traffic Survey



7.2 Study Poster

7.3 Ethics Board Approval

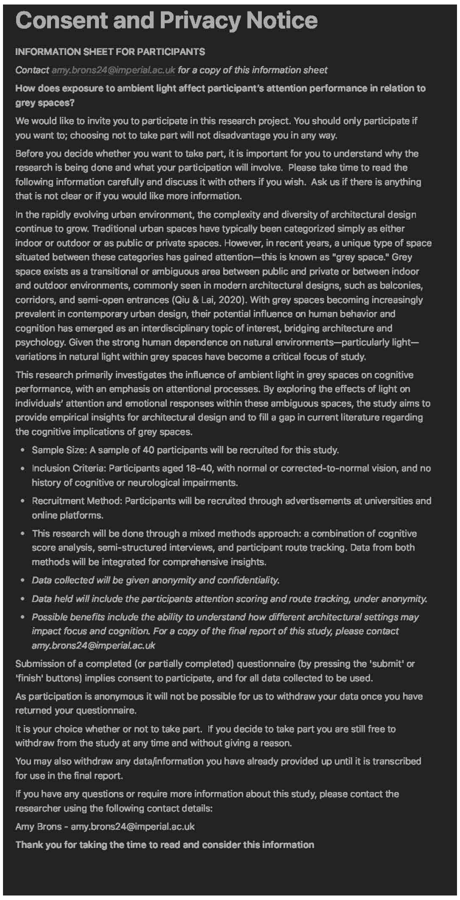
Approval can be viewed by members of Imperial College London, here: Link
https://imperiallondon.sharepoint.com/sites/foe/designeng/EthicsApproval/Lists/Ethics
%20Approval1/DispForm.aspx?ID=410&pa=1&e=3Tl6d4

For further information, please contact the research team.

7.4 Semi-Structured Interview Questions

- How likely are you to walk through here during your day?
- What positives can you draw from this space?
- What negatives do you find in this space?
- How does the lighting of this space affect your perception?
- How could this space be improved?

7.5 Consent and Privacy Notice



Consent and Privacy Notice

INFORMATION SHEET FOR PARTICIPANTS

Contact amy.brons24@imperial.ac.uk for a copy of this information sheet

How does exposure to ambient light affect participant's attention performance in relation to grey spaces?

We would like to invite you to participate in this research project. You should only participate if you want to; choosing not to take part will not disadvantage you in any way.

Before you decide whether you want to take part, it is important for you to understand why the research is being done and what your participation will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or if you would like more information.

In the rapidly evolving urban environment, the complexity and diversity of architectural design continue to grow. Traditional urban spaces have typically been categorized simply as either indoor or outdoor or as public or private spaces. However, in recent years, a unique type of space situated between these categories has gained attention—this is known as "grey space." Grey space exists as a transitional or ambiguous area between public and private or between indoor and outdoor environments, commonly seen in modern architectural designs, such as balconies, corridors, and semi-open entrances (Qiu & Lai, 2020). With grey spaces becoming increasingly prevalent in contemporary urban design, their potential influence on human behavior and cognition has emerged as an interdisciplinary topic of interest, bridging architecture and psychology. Given the strong human dependence on natural environments—particularly light—variations in natural light within grey spaces have become a critical focus of study.

This research primarily investigates the influence of ambient light in grey spaces on cognitive performance, with an emphasis on attentional processes. By exploring the effects of light on individuals' attention and emotional responses within these ambiguous spaces, the study aims to provide empirical insights for architectural design and to fill a gap in current literature regarding the cognitive implications of grey spaces.

- Sample Size: A sample of 40 participants will be recruited for this study.
- Inclusion Criteria: Participants aged 18-40, with normal or corrected-to-normal vision, and no history of cognitive or neurological impairments.
- Recruitment Method: Participants will be recruited through advertisements at universities and online platforms.
- This research will be done through a mixed methods approach: a combination of cognitive score analysis, semi-structured interviews, and participant route tracking. Data from both methods will be integrated for comprehensive insights.
- *Data collected will be given anonymity and confidentiality.*
- *Data held will include the participants attention scoring and route tracking, under anonymity.*
- *Possible benefits include the ability to understand how different architectural settings may impact focus and cognition. For a copy of the final report of this study, please contact amy.brons24@imperial.ac.uk*

Submission of a completed (or partially completed) questionnaire (by pressing the 'submit' or 'finish' buttons) implies consent to participate, and for all data collected to be used.

As participation is anonymous it will not be possible for us to withdraw your data once you have returned your questionnaire.

It is your choice whether or not to take part. If you decide to take part you are still free to withdraw from the study at any time and without giving a reason.

You may also withdraw any data/information you have already provided up until it is transcribed for use in the final report.

If you have any questions or require more information about this study, please contact the researcher using the following contact details:

Amy Brons - amy.brons24@imperial.ac.uk

Thank you for taking the time to read and consider this information

7.6 Survey Welcome Page

Hello! Welcome to our survey!

Thank you for participating in our study!

Before getting started, please ensure you have read our ethics and privacy form here: . Your information will be anonymized, and your data will be secure!

Consent and Privacy Notice

You MUST be 18 or older to participate in this study.

If you have any questions regarding this or any part of this study, please contact amy.brons24@imperial.ac.uk

Instructions

Step One:

On your own, please track your route through campus over the course of a day. Keeping a sketch or mental note of all the places you visited may be helpful. After you have left campus for the day, continue to step 2.

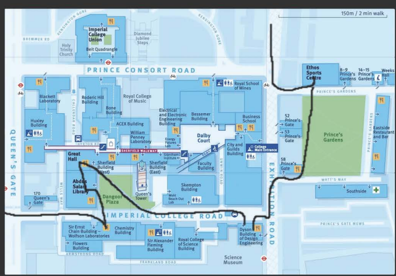
Step Two:

Draw your route here (PLEASE COMPLETE THIS PART OF THE SURVEY ON A LAPTOP!)

Try and adjust the brush sizes to be as accurate as possible.

LINK: https://pollunit.com/polls/zxz9p0icoxnqmp3y2lsnma

Sample of what this will look like.



Step Three:

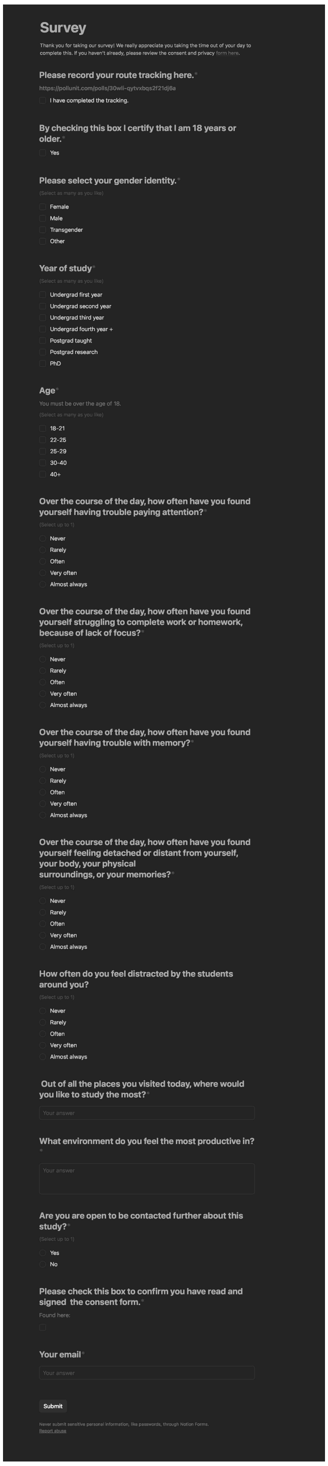
Complete this survey here.
LINK: https://cottony-chef-be8.notion.site/1305c236800980dc925ef021b09c24e2?pvs=105

Make sure to include a working email address (preferably Imperial) to be considered to win **£100 Amazon gift card!** (You must do all the steps of the survey to be considered)

Step Four:

That's it! We thank you so much for your help!

7.7 Survey Questionnaire



Survey

Thank you for taking our survey! We really appreciate you taking the time out of your day to complete this. If you haven't already, please review the consent and privacy form here.

Please record your route tracking here.*

https://pollunit.com/polls/30wli-qytvxbqs2f21dj6a

- [ ] I have completed the tracking.

By checking this box I certify that I am 18 years or older.*

- [ ] Yes

Please select your gender identity.*

(Select as many as you like)

- [ ] Female
- [ ] Male
- [ ] Transgender
- [ ] Other

Year of study*

(Select as many as you like)

- [ ] Undergrad first year
- [ ] Undergrad second year
- [ ] Undergrad third year
- [ ] Undergrad fourth year +
- [ ] Postgrad taught
- [ ] Postgrad research
- [ ] PhD

Age*

You must be over the age of 18.

(Select as many as you like)

- [ ] 18-21
- [ ] 22-25
- [ ] 25-29
- [ ] 30-40
- [ ] 40+

Over the course of the day, how often have you found yourself having trouble paying attention?*

(Select up to 1)

- Never
- Rarely
- Often
- Very often
- Almost always

Over the course of the day, how often have you found yourself struggling to complete work or homework, because of lack of focus?*

(Select up to 1)

- Never
- Rarely
- Often
- Very often
- Almost always

Over the course of the day, how often have you found yourself having trouble with memory?*

(Select up to 1)

- Never
- Rarely
- Often
- Very often
- Almost always

Over the course of the day, how often have you found yourself feeling detached or distant from yourself, your body, your physical surroundings, or your memories?*

(Select up to 1)

- Never
- Rarely
- Often
- Very often
- Almost always

How often do you feel distracted by the students around you?

(Select up to 1)

- Never
- Rarely
- Often
- Very often
- Almost always

Out of all the places you visited today, where would you like to study the most?*

Your answer

What environment do you feel the most productive in?*

Your answer

Are you are open to be contacted further about this study?*

(Select up to 1)

- Yes
- No

Please check this box to confirm you have read and signed the consent form.*

Found here:

- [ ]

Your email*

Your answer

Submit

Never submit sensitive personal information, like passwords, through Notion Forms.
Report abuse

7.8 Light Meter

The light meter used is called the*Mcbazel Digital Illuminance Light Meter, with Lux Meter Range up to 200,000 Lux*, and can be found here

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