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Beyond Depth Cues

Lighting and visual complexity as factors in navigation

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ABSTRACT

Spatial configuration is central to Space Syntax modelling, either implicitly in methods such as axial line analysis (Hillier & Hanson 1984; Hillier 1996), or explicitly in visibility graph analysis (Turner *et al.*, 2001) and visual agents (Penn and Turner, 2001), and in fundamental spatial principles on which these are based (Benedikt, 1979). Its effect on movement via individual navigation is mediated by the capacity of human vision, as demonstrated in observations of the link between visual fixation and route selection (Emo, 2014). Vision, however, is frequently unable to perceive spatial configuration accurately (McElhinney *et al.*, 2022), and may be affected by other aspects of the environment with relevant influence on movement, which are not currently accommodated by Space Syntax models.

This paper investigates two variables distinct from spatial configuration, light intensity and surface complexity, for their effect on route choice. A 3D game-like environment, implemented through Grasshopper within Rhino3D, was used to record the behaviour of human navigators exploring an irregular pattern of orthogonally placed, intersecting corridors, for which both light and complexity were varied. Routes were recorded for each journey, and gaze monitored using an eye-tracking headset developed for this experiment.

Results reveal relationships between each of the variables and gaze, and between gaze and subsequent path choice. Compared with a baseline of all possible isovists within the environment, the gaze distribution of participants for all experiments has more distant mean and peak values, and this is most distant when light is varied. Movement, as assessed by path choice at corridor junctions, shows an expected overall correlation with path angle, but the relationship with other spatial variables, such as visible distance, varies significantly across the experiment when light and complexity variables are changed. Both variables are seen to correlate positively with paths chosen, with the effect of surface complexity being stronger when both are varied simultaneously. A causal chain can be inferred that suggests higher relative light levels draw the

visual attention, and one or both of these then positively influence the choice of route in that direction.

KEYWORDS

Visible distance, lighting, complexity, perception, navigation, eye-tracking

1 INTRODUCTION

Space Syntax methodology has long been foundational in the analysis of spatial configurations. Utilising key spatial principles, such as visible distance, connectivity, and integration among other configurational properties, in understanding movement patterns in the built environment (Penn and Turner, 2001; Turner *et al.*, 2001; Turner *et al.*, 2005). However, recent research suggests that additional environmental factors (Langenfeld *et al.*, 2013; McElhinney *et al.*, 2022), such as light and surface complexity, may influence route choice, yet remain largely unexplored within the Space Syntax framework. As such, there exists gaps in our understanding of how other variables, specifically non-spatial variables, might affect how we make decisions when moving through space. Furthermore, understanding whether these non-spatial variables influence movement directly, or indirectly via a cognitive process. This paper addresses this gap by investigating how these non-spatial variables affect our perception and movement within a space, and whether there is a causal relation between our perception and our movement within said space.

The role of vision in navigation cannot be understated, as evidenced by the link between visual fixation and route selection (Emo, 2014). It is acknowledged that human perception can be affected by various environmental factors which in turn contribute to our perception of spatial depth and form (Marr, 1982). In his computational theory of vision, Marr explores how low-level visual features involved in the image processing of the brain also form an important part of the signals upon which the higher-level cognitive decision-making process acts. Therefore, it is essential to consider factors beyond spatial configuration in this context. The paper focuses on examining these effects at the lower level of cognition, to gain insights into the immediate perceptual processes and basic decision-making mechanisms underlying navigation.

In this study, it is hypothesised that low-level visual cues, including light and surface complexity, will influence decision-making processes during navigation within a novel environment. It is inferred that these low-level visual features exert a direct influence on the higher-level cognitive process involved in decision-making when navigating in unfamiliar spaces. This would suggest that the relevance of low-level visual cues lie in their capacity to convey information essential for interpreting and navigating the surrounding environment effectively.

This will be further supported by the study of the gaze in relation to the decisions made by the individual when navigating. The hypothesis posits that low-level visual cues will have an impact on the time participants spend fixating on different choices during a decision-making task, and thus influence the decision made. Participants will be therefore more likely to choose the option they spend the most time fixating upon, indicating that low-level visual cues play a subconscious role in decision-making.

This is tested through a series of participant-based empirical spatial experiments, conducted within a virtual 3D-environment for apt control and data recording. Analysing the role of these select cues when decision-making during navigation to establish whether they are meaningful, and bear weight over the actions we take. In essence, the systems being tested for are significant in that they are the building blocks of semantics and higher-level cognitive processes; they are what guide us and allow for us to informed decisions. Therefore, working to provide a greater understanding of factors like visual complexity, light, and gaze behaviour, will allow us to better understand their effect upon more complex high-level decision-making.

To explore theses variables, a novel experimental setup was employed, utilising a 3D virtual environment wherein participants navigated through intersecting corridors with varying levels of light and surface complexity. By recording participant's gaze patterns and route choices, this study aims to elucidate the relationships between environmental features, visual attention, and route selection. The findings are expected to provide insights into the complex interplay between these non-spatial variables and human navigation behaviour. Additionally, to ensure a focused examination of the influence of low-level visual cues, measures were implemented to minimise the influence of potential confounding variables such as memory and landmark recognition, as these higher-level cognitive processes have been shown to significantly impact navigation (Garling, Book and Lindberg, 1986; Conroy-Dalton and Bafna, 2003).

2 THEORY

In the study of spatial configuration and navigation within built environments, understanding the role of low-level visual cues is important. Among these cues, light intensity and surface complexity stand out as directly visible, non-spatial components likely to influence spatial perception. These features not only affect the visibility and legibility of spatial layouts, but also attract attention and influence our perception of depth, scale, and form (Marr, 1982, p. 41). Similar studies have previously explored the role of non-spatial variables, such as 'visual attractiveness' on navigational behaviours and found them to have juxtaposed predicted syntactic behaviours (Langenfeld *et al.*, 2013).

Eye-tracking technologies will be used to investigate whether navigational decisions are directly influenced by these low-level visual cues pre-attentively or rely on higher-level cognitive processes. Measuring participants visual attention as they interact with experimental stimuli will help to distinguish between decisions influenced by low-level perceptual information and those driven by higher-level cognitive processes.

2.1 Light Intensity

Light intensity has a direct association with the signal intensity received by the retina and bares weight as the fundamental baseline upon which we can make navigational judgements. Increased light levels enhance signal contrast, increasing our ability to detect zero-crossings in the signal gradient and thereby improving the perception of edges, form, depth and subsequent spatial configuration, this is known as visual acuity (Frisby, 2011, p. 89). However, both insufficient and excessive light can impede the construction of an accurate spatial image due to inadequate information availability, and as a result we are less confident in the presented information and less likely to act upon it (Marr, 1982, p. 259).

Prior research into the effects of lighting on route choice have typically been explored within real-world contexts (Unwin, Symonds and Laike, 2016). A benefit of conducting these observations within a virtual environment lies in the control over the semantic influence of light levels on navigation. Typically, darker spaces would be avoided by an individual due to an association of darkness with danger, uncertainty, and negative emotional responses, such as fear and anxiety, as explored extensively in studies involving the effects of lighting on pedestrian movement (Fotios, Unwin and Farrall, 2015). However, the safety and controlled nature of the virtual environment allows participants to act independently of these factors, or at the very least at a reduced level, allowing us to better understand light's role in non-semantically influenced navigation and decision-making.

2.2 Visual complexity

The role of visual complexity is explored as a general umbrella term for the role of retinal signal intensity brought about by the quantity of edges, zero crossings, contrast, and boundaries in the initial stages of visual processing (Marr, 1982, p. 37). The choice to investigate this feature is because, much like light intensity, it directly effects the level of information present for us to make decisions in an environment. In this case, we might expect visual complexity to affect decision-making through two separate means. One is that visual complexity allows us to further explore the role of cognitive load and stress introduced by an overabundance of visual information, wherein too much complexity might be seen as less desirable as the information takes longer to process. This is demonstrated in studies on the sensory memory and cognitive load theory (Sweller, 1988), indicating that people would prefer a reduced quantity of visual information, provided there is enough visual complexity and sufficient light present in the environment to determine depth and navigate effectively, but not too much that it obscures our ability to construct a 3D spatial representation of the environment. Which could instead result in phenomenon like visual crowding (Whitney and Levi, 2011).

Alternatively, the use of more visually complex environments might also result in navigational behaviour associated with reduced intelligibility and perception of visible distance, both key features utilised in Space Syntax models. When navigating, space-geometric measures like the sky area and floor area have been shown to play a key role in determining the axial lines, presented within a spatial configuration, as shown in empirical VR studies of this nature (Emo, 2014). Visual complexity possesses the ability to disrupt the detection of the ground and sky-areas through the discontinuity of shape contours (Marr, 1982, p. 215) present in a scene. The abundance of what is known as an occluding contour (Marr, 1982, p. 218), a type of discontinuity involved edge detection, might impact our ability to judge the connectivity of a space, meaning that an individual may be less likely to take this route.

Additionally, the presence of significantly contrasting visual complexity or light may also form more visually salient areas through a phenomenon referred to as 'visual pop outs' (Treisman, 1986), a pre-attentive lower-level visual process. This captures our attention through the selection process and influences our decision-making.

2.3 Visible Distance (Depth-Cues)

The use of visible distance in various Space Syntax isovist models, is well documented (Turner and Penn, 2002). The inherent tendency of these agents is to choose directions that offer greater visible distance, which often correlates with the larger areas and indicates higher connectivity. It has also been found that this direct exosomatic information used by these isovist models correlates with human navigational behaviour (McElhinney *et al.*, 2022). From this, we can infer that visible distance may influence participant choice behaviour, especially in its relationship with environmental visibility. This makes it an important metric to consider alongside the identified non-spatial variables, due to its relationship with our perception of spatial configuration. Serving as a reference point upon which the non-spatial variables can be assessed in relation to.

3 DATASETS AND METHODS

3.1 Experimental context

The experiment conducted involved 15 participants, who were tasked with locating a goal object within 3 differently configured virtual corridor networks, each composed of 50 differently sized corridors. Corridors were placed orthogonally so that all turns were an identical 90 degrees, in part to control for the spatial variable of angle impacting route choice. This resulted in a total of 45 datasets (3 per participant), with over 1800 decisions being made at junctions and intersections across all participants during the study.

During the experiment, participants are placed randomly in 1 of 3 possible maps and asked to locate a goal object (a red sphere), which they are informed is also randomly placed in the environment. The participants are not shown the overall map composition and are unaware of both their starting location and the position of the goal object. This is to mitigate the influence of higher-level cognitive influences from impacting the participants performance. The participant then repeats this process in the remaining 2 maps, with the conditions in each map varying each time the participant performs the task. One map varying light intensity and corridor lengths, one varying visual complexity and corridor lengths, and one map presenting light, complexity, and varied corridor lengths together. The assigning of each map to the experiment type (light, complexity, both) is random for each participant to reduce the effect of the maps composition on the decisions made. Before the experiment, each participant is assigned a ‘seed value’, which is input into the scripts to generate random start and goal locations for each of the three maps, providing a traceable pseudo-random variable.

As the nature of the search task would typically result in participants strategizing to avoided revisiting the same areas, efforts were made in the design of the experiment to (a), limit the time spent in the environment to less than the time required to explore it entirely, to avoid forming a complete mental representation. And (b), not exposing the participant to the same environment more than once. Alongside this, the representation of surface complexity was designed to avoid the formation of memory association and landmark recognition.

Considering the level of control required within the experimental environment and data being recorded, a bespoke game-engine and 3D computer-generated environment were developed to optimise data tracking and control. This environment has been developed by the authors through a combination of Grasshopper, configured in C# and .NET VB, and the Python scripting language within the Rhino3D CAD application. Utilising the realtime rendering engine VRay

Vantage developed by Chaos, to render the environment which the participant views and navigates within (**Figure 2**).

The value of utilising a goal-oriented task while navigating, despite not tracking for navigational efficiency or time spent, was to encourage to participants to actively explore and navigate the space, incentivising them to make decisions naturally, while providing a level of abstraction from the primary intentions of the research. This was built upon the choice-clue wayfinding model devised by Martin Raubal (Raubal and Egenhofer, 1999, p. 7) for studies concerning navigation in the built environment. Choices referring to the decision points in wayfinding, namely the junctions and intersection, and the possibilities presented at each, alongside the clues, which are the variable conditions presented to the participant at these moments.

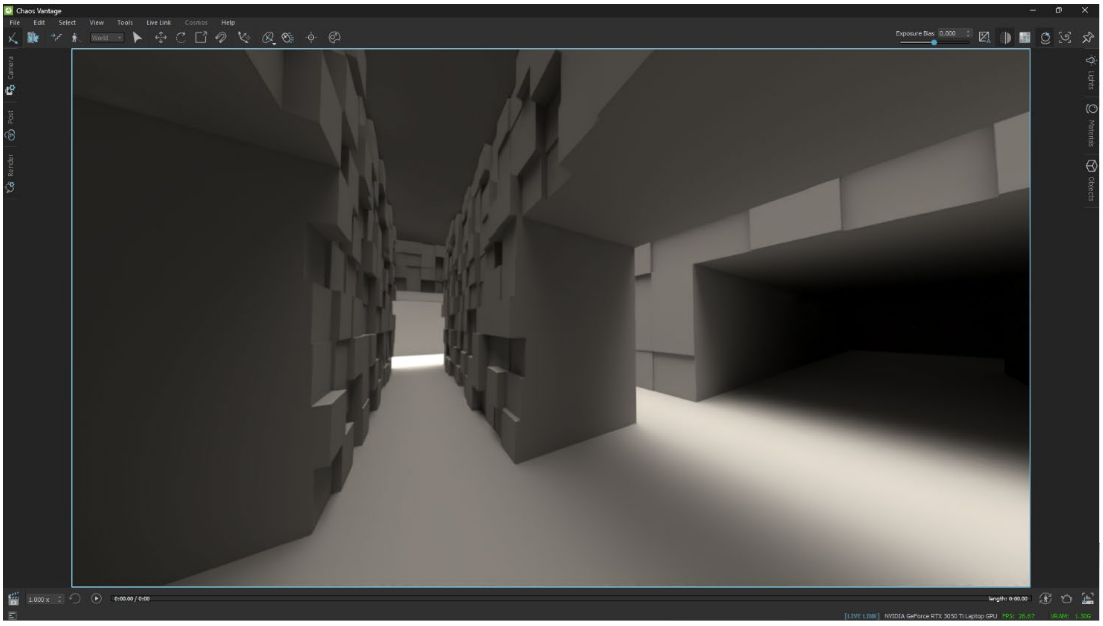


Figure 1 A screen capture from Chaos Vantage depicting what the participant is viewing during the experiment.

3.2 Game engine system and benefits of using a 3D computer-generated environment.

Utilising a computer-generated environment facilitated an adequate level of control, replication and the ease of data collection and analysis (Dombeck and Reiser, 2012). This is particularly relevant in this study, wherein the space must be designed with aims to reduce one's ability to both drawn upon and attach memory to the space. Participants are thus incentivised to make decisions based on the limited information supplied and invoke a decision-making process derived from low-level visual cues, while mitigating the effects of semantic and high-level cognitive influence over the space. For example, if one were to utilise a real-world environment, extraneous variables, and inconsistencies within said environment, such as sounds or defects, might influence their decision-making process. Limiting the variables as much as possible, while still providing enough information to elicit a more natural response to the stimulus within a direct context, suggests that the data gathered would be more conducive to decisions made within a real-world environment.

3.3 Experimental metrics

While typical considerations in navigational tasks may include metrics like the time to complete the task and consideration of overall route taken to the goal object, we are concerned with how low-level visual cues influence the decisions made in an environment on an options-choice basis. Thus, instead of considering how these factors might affect navigational efficiency, we consider the impact these factors have on decision-making to establish the weight each variable bares. The metrics are outlined as follows:

Decisions made at junctions: At each junction or intersection, the possible options that can be selected by the participant and the choice made are recorded, alongside the presented values of light, visual complexity, or depth (visible distance). Other recorded measures include the angularity, choice order, choice type (intersection/junction) and the conditions the participant originated from.

Eye-tracking data: The eye-tracking data is used to infer the distribution of the gaze across the options and decisions made on a qualitative level, but also to assess the distribution of the gaze across the differing conditions. Furthermore, we can also investigate navigation behaviour through gaze depth to establish how each variable affects our perception of a space.

Angularity and Map Design: While studies into the effects of angularity in route choice (Dalton, 2003), specify that route choice trends towards a minimal change in angularity when navigating, we have designed the virtual environment within an ortho-linear grid. This also affects visibility, wherein the forwards condition at an intersection or junction would present greater immediate visibility despite not necessarily being the greatest visible distance. While this may result in that the navigator choosing to proceed forwards more frequently, rather than take a 90-degree turn, the experiment will maintain a better architectural relationship with the nature of the built environment.

3.4 The Grid System and Map Generation Script

The maps generated through the script abide to a 100 by 100-meter grid system, with a minimum corridor width and depth of 2 metres. Having a minimum distance present prevents corridors forming too close to each other and resulting in decisions being made too hastily. Generating the maps upon a grid system allows for easier parametric scripting and generation of the visual complexity and lighting variables. This also provides the ability to analyse the data using a simple grid cell system, denoting the possible decisions that could be made at a junction.

The maps are generated from a simulated network of lines from random seed values through the substate algorithm (Tarbell, 2003). The generated line network is then offset by a randomly assigned value or 2, 3, 4 or 5 meters to determine the corridor width, and extruded by an integer value of 3, 4, 5 or 6 to determine height. The random variation of the corridors width and height are implemented to provide more natural variation to the environment, thus make the space more comparable to a natural setting. 3 Individual maps are generated through the script, each with 50 corridors in a randomised arrangement. Ensuring a varied set of conditions while maintaining a consistent level of overall navigational complexity through each map. By nature of the algorithm used to generate each map layout, the length of the corridor positively correlates with how well connected the corridor is.

A plain, grey palette by each map, designed to mitigate unwanted colour variance in the map, reduces the involvement of the semantic influence of colour in the experiment. The intention was to develop a novel and unfamiliar environment, while still abiding to a standardised architectural logic.

3.5 Visual Complexity

The generation of a controlled and measurable level of visual complexity was achieved through the manipulation of the density of edges, orientation, and resulting contrast fluctuation. This process informed the use of a regular grid system and ortho-linear map composition, which allows the map to be subdivided iteratively to break up the surface geometry. The subdivided walls are then randomly extruded to values relative to the subdivisions, resulting in an incremental increase in the level of visual complexity and thus signal intensity. This method ensures an abstract, but consistent and traceable level of visual complexity to be implemented, without providing so much variance that participants would be able to differentiate individual corridors from one another, whilst also ensuring that the depiction of complexity mitigates any similarity to recognisable forms. This could assist participants in recognising areas which they have already explored through landmark formation and recognition. Each corridor in the map is assigned a subdivision value of either 0, 1, 2 or 4 subdivisions, 0 representing no additional complexity (**Figure 2**).

3.6 Lighting Control

The corridors generated by the map generation script have their top-most face used to generate rectangular directional lights through VRay, providing a consistent lighting condition throughout each corridor. Using a random number generator, stepped values of 1%, 33.3%, 66.6%, or 100% lighting intensity, are assigned randomly to the rectangular lights (**Figure 2**). With 66.6% lighting intensity being considered a well-lit corridor, 1% being almost entirely pitch black, 100% presented as an upper bound or 'brighter' than necessary condition. When, testing for visual complexity in isolation, light level 3 was used uniformly to maintain a consistently 'well-lit' condition throughout the environment.

The lighting itself is rendered through Chaos Vantage, a real-time raytraced visualisation engine. Allowing for the realtime calculation of light bounces using a GPU to provide a far more accurate lighting set-up than typical lighting engines.

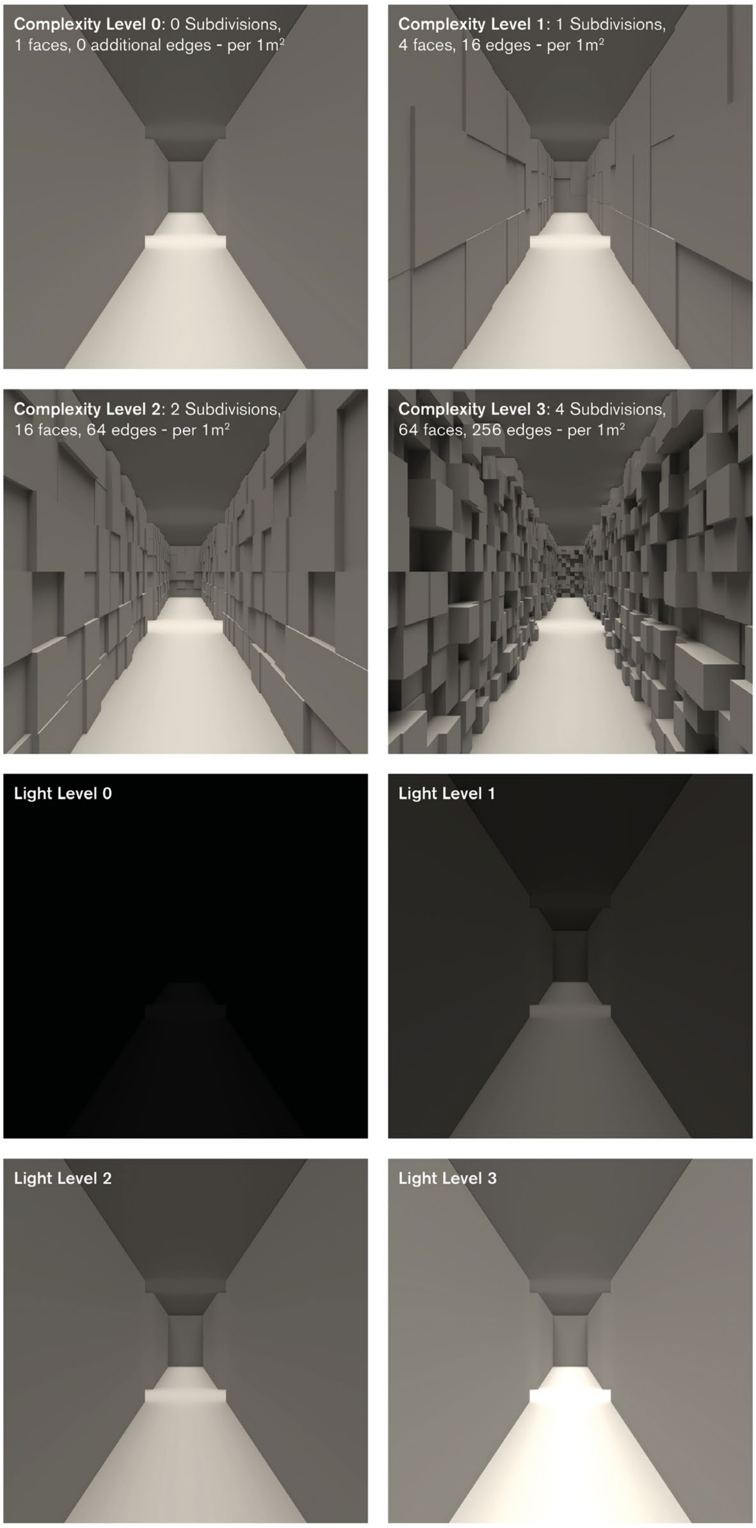


Figure 2 Corridor light and complexity levels as presented to participants in the experiment

3.7 Eye-tracking and Mapping

A custom eye-tracking headset and 3D mapping tool was developed upon the PupilLabs framework in Python and Grasshopper for use in the experiment. This allows for the implementation of eye-tracking and it's mapping in realtime across 3D space.

This process operates using April Tags (Olson, 2011), a fiducial marker system, to define the bounds of a surface captured by the eye-tracking headset and map the eye-tracking data as a normalised coordinate. In this circumstance, the surface tracked is the bounds of the computer monitor the participant views while navigating in the experiment. The participants virtual viewport bounds and positional are tracked within Grasshopper as a physical geometry instance. From here, the tracked viewport surface is evaluated with the normalised coordinates sent from the headset to the Pupil Core host application, and then to the receiver script in Grasshopper. This now presents us with two points; the camera (user) position and the gaze's location on the viewport. A vector is calculated between these two points and is used to project the gaze's location upon the physical geometry in the scene.

Each participant was calibrated to the headset prior to each experiment to maintain accuracy, for a total of 3 times. If the calibration resulted in a gaze tracking accuracy of >2 degrees, the calibration process was repeated until the accuracy was <2 degrees.

3.8 Game-engine Script

A simple game engine was developed in Grasshopper to allow for the use of a game-controller input system within the experiment and basic physics, through a series of transformations to control the camera location and target within the Rhino3D virtual environment. This input method was chosen for its simplicity and accessibility for the participants.

The viewing angle of the virtual camera was of primary concern, as it directly affects the perception of options presented to participants at each junction. Optimally, the 170-degree FOV utilised by the EVA-agents developed by Turned and Penn would be utilised, as they found that these agents perform most similarly to humans in navigational tasks (Penn and Turner, 2003). This corresponds with existing research into the real-world FOV of the human visual field of around 210-degrees (without eye-movement). However, when presented in a virtual environment on a flat display, a viewing angle of 170-degress distorts the view substantially, which would in turn impede participant performance. As a result, a horizontal viewing angle of 130-degrees was utilised, striking a good visual balance between distortion and visibility, while providing slightly more information than the 114-degree horizontal binocular visual field of humans (Howard and

Rogers, 1995). This was informed by an investigation into the minimum FOV for user search tasks in 3D virtual environments (Osman et al., 2014), which recommends a minimum FOV of 30-degrees, with no substantial difference in task performance between 30-degrees through 110-degrees. However, this must be considered when interpreting data, as in a real-life context, decisions could alter based on cues presented within the peripheral vision.

3.9 Data Processing and Analysis

To analyse the participant data, a suite of scripts were developed in Grasshopper and linked to Microsoft Excel to assess the participant data accurately and consistently across all conditions. One set of scripts analysed the participant gaze behaviour, while another set looked solely at the decisions made at junctions and intersections by each participant. Assessing the conditions of the corridors presented alongside each decision, including a categorisation of the options presented, the choice made, and the condition the participant is currently in. The recorded conditions included the variable value (light/complexity), the length of each corridor, the angularity of the choice and which corridors were observed as well as how long each option was considered as a percentage distribution. Certain contextual data, such as the angularity and view-depth had to calculated at each junction individually, as this data varied depending on the approach direction of the participant.

The gaze data was processed in tandem with the positional data. The 3D gaze data was mapped onto the space via a vector between the user locations (camera location) and the gaze point. The projected gaze points were then used to assess relevant gaze data involved in the decision-making process, such as the corridors which were observed during the decision-making process and the distribution of time spent looking at each option. This was calculated by taking the gaze data from 2 decisions prior through to the decision point (the junction or intersection) and calculating the distribution of intersections between the gaze path and openings of each corridor at the decision point being evaluated (**Figure 3**).

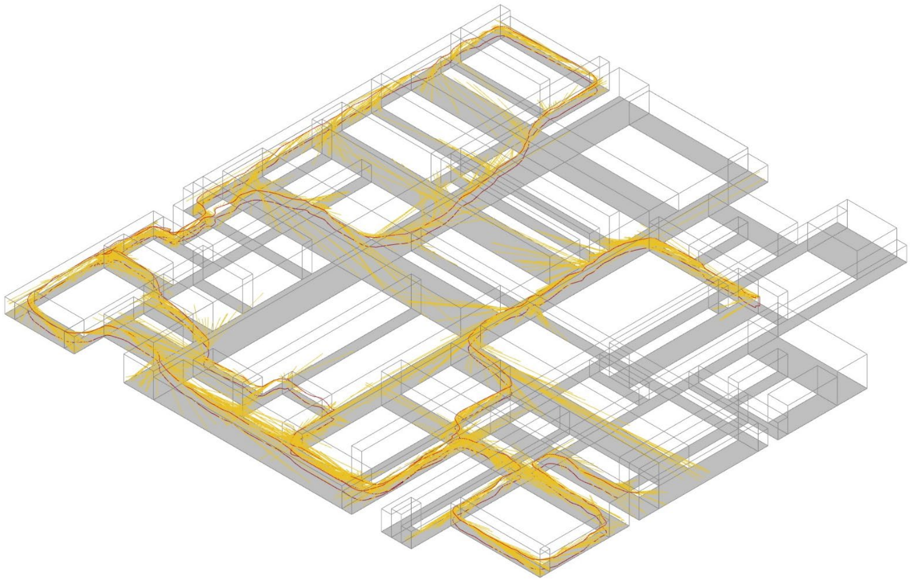


Figure 3 An example of the 3D gaze data (yellow), and the participant route choice (red) for the lighting experiment of map 1.

4 RESULTS

4.1 Choice Based Decision Making Statistics

The main body of the analysis was conducted by assessing the choices made by each participant at each junction or intersection. The data was processed to consider the choice as normalised relative to the presented options at each decision point, again relative to the frequency the options appeared. Any choice involving a backwards decision was omitted from this analysis. This decision was informed by an analysis of the normalised mean angularity choice distribution made by the participants across all experiments, which found participants only opted to move backwards 1.49% of the time during the study.

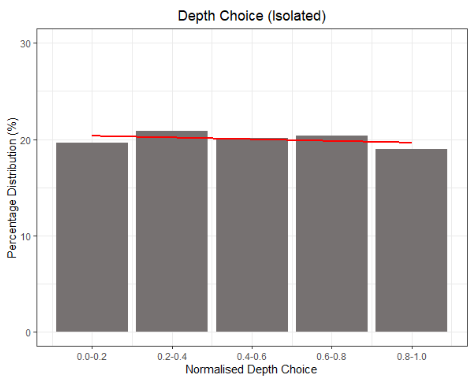
Angularity	***% Distribution***
Backwards	1.49%
Right	30.49%
Left	31.77%
Forward	36.24%

This data acts as an important control variable in showing there to be a rough symmetry between angularity selection. While much Space Syntax precedent (Turner and Penn, 2002; Hillier and Iida, 2005; Hanna, 2021) would suggest that angularity has a greater impact on route choice, this data shows that this isn't the case in this rectilinear 3D virtual environment, and therefore we can concentrate on the other variables presented in this experiment.

To assess the effect of visual complexity and lighting across the experiments, the data each at decision point was normalised, remapping the values between 0-1 across the measured variables to assess the relative weighting of the choice to the presented variables at each choice area. Additionally, this allows trends to be gauged across the different data sets. The normalised data was sorted into frequency bins to judge the extent to which a participant was making the choice to move into a condition relatively greater or less, proportionally to the presented options. Again, the bin frequency was calculated relative to the frequency at which the bins appeared to each participant, thus accommodating for decisions which were made because they appeared more frequently. Bins of .2 intervals were chosen due to the limited range of normalised data present by the 4 (0,1,2,3) varying conditions, despite the continuous nature of spatial variables, such as visible distance, allowing trends in the data to be seen more clearly.

This process also allows us to assess the effects of spatial variables, such as visible distance in navigation, by parcelling instances in each experiment where no variability in light or complexity is presented at an intersection or junction, but a variation in visible distance is. This provides further insight into whether the behaviour of agent movement flow, which have been shown to demonstrate a bias towards greater visible distance (Penn and Turner, 2001), correlates with human navigational behaviours within this experimental environment.

These occurrences appear in the experiment where a participant is presented with either a T-Junction type decision, or certain intersections, as the complexity and light levels vary by corridor ID. Therefore, while at these junctions these complexity or light level will remain constant, the visible distance will vary. With a choice sample size of 445 it was found that participants in this particular experimental set-up displayed no preference towards greater visible distance in their decision making (**Figure 4a**). While work on Syntax agents (Hillier and Iida, 2005) and gaze behaviour in VR (Emo, 2014) suggest a bias in many environments towards the longest line of sight, this was found not to be the case within the controlled nature of this specific search task and environment. The fact that it was not, suggests again that we are able to read differences in the non-spatial variables that follow without being confounded by these variables.



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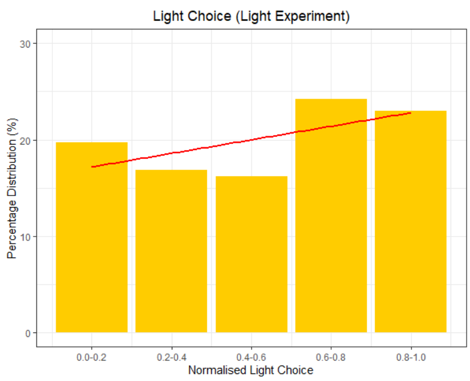

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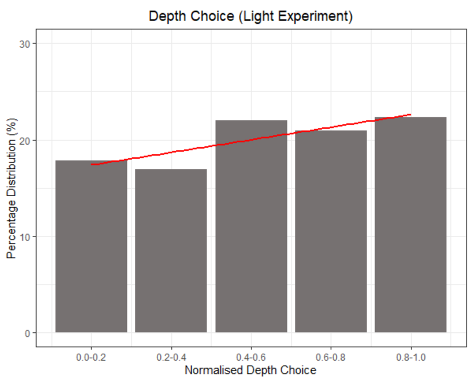

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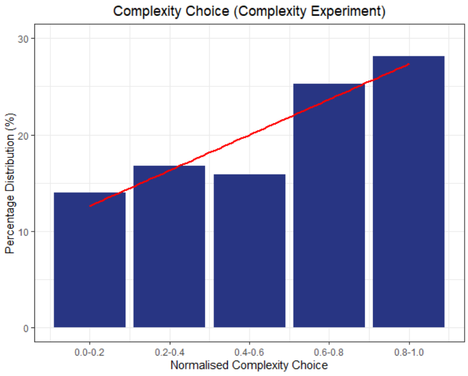

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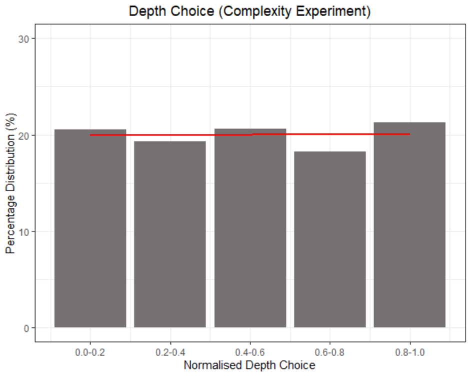

(e)

Figure 4 Normalised distribution of relative light (yellow), complexity (blue) and depth (grey) chosen by participants in the in each experiment type. The x-axis denotes the relative magnitude of the bin value, with bins below 0.4-0.6 (centre) indicating a relative 'less than' choice, the central bin indicating that participants chose a relative 'middle ground', and the bins greater than 0.4-0.6 indicating a relatively 'greater than' choice. The y-axis denotes a normalised percentage distribution of the selection. Lines of best fit are shown in red.

Figure 4b and **Figure 4c** present interesting data when considering the light in contention with depth. With the lighting trend-line contending roughly equally with depth during navigation. This behaviour might be explained by the reduced level of information presented at low-lighting conditions, requiring participants to select longer, more well-lit corridors. However, participants did opt for a relatively unchanging depth-choice more frequently, indicating a more balanced influence of corridor length. Perhaps due the varying intelligibility presented by the varied lighting conditions. In the complexity experiment (**Figure 4d, Figure 4e**), participants exhibited no preference for visible distance and a strong preference for greater complexity. While it might be expected for participants to opt for less complex routes, where corridor entrances are not occluded by the surface complexity, and it is easier to infer depth and assess the intelligibility of a space, this appears to not be the case in this instance. This could be a result of the visual saliency of the more complex corridors (Treisman, 1986).

This is particularly apparent when assessing the experiment where participants were presented with both light and complexity variables. With participants trending towards relatively shorter corridors and greater complexity, prevailing over the influence of light intensity, and resulting the in more irregular data shown in **Figure 5**. This could be a result of the combined effects and resulting reduced intelligibility of the space presented by the varying lighting and complexity conditions.

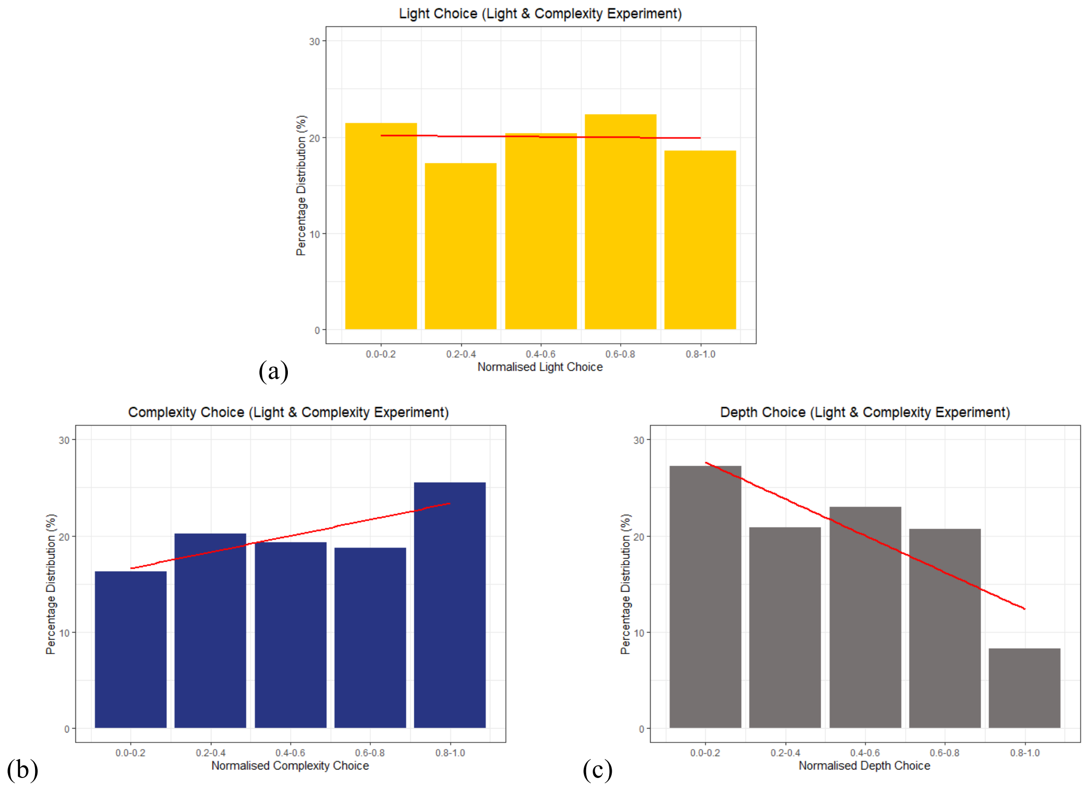

Figure 5 Normalised distribution of relative light (yellow), complexity (blue) and depth (grey) chosen by participants in the lighting & complexity experiment. The x-axis denotes the relative magnitude of the bin value, with bins below 0.4-0.6 (centre) indicating a relative ‘less than’ choice, the central bin indicating that participants chose a relative ‘middle ground’, and the bins greater than 0.4-0.6 indicating a relatively ‘greater than’ choice. The y-axis denotes a normalised percentage distribution of the selection. Lines of best fit are shown in red.

4.2 The Role of the Gaze in High-Level Cognitive Decision Making

The analysis also incorporated the nature of the participants gaze to evaluate the gaze behaviour in response to the conditions of each experiment. One example of this is gaze distance, calculated by measuring the distance between each fixation and the participants location in all candidates across the three experiments. To assess the expected mean expected gaze depth across the experiments, an isovist control placed randomly at 1000 different points in each map and measured the possible gaze depth in increments of 10 degrees. The result indicated a mean gaze depth of 6.45 meters. The mean depths across the experiments loosely correlate with this control mean, with the lighting experiment trending towards a greater than expected mean gaze depth.

However, **Figure 6** reveals that the gaze-distance distribution does not align with the isovist control. The isovist control's simulated gaze is uniformly distributed in all directions, which combined with the layout of the map's narrow corridors, results in data peaking in the 1m bin. However, the navigational task necessitates searching down the length of the corridors for the goal object, implying optimal search strategies should entail longer gaze distance. Hence, we see peaks in the 4-5m bins for the participants, which coincides more closely with this mean.

Experiment Type	***Mean Gaze Distance***
Complexity	6.66m
Control	6.45m
Light	7.44m
Light & Complexity	6.23m

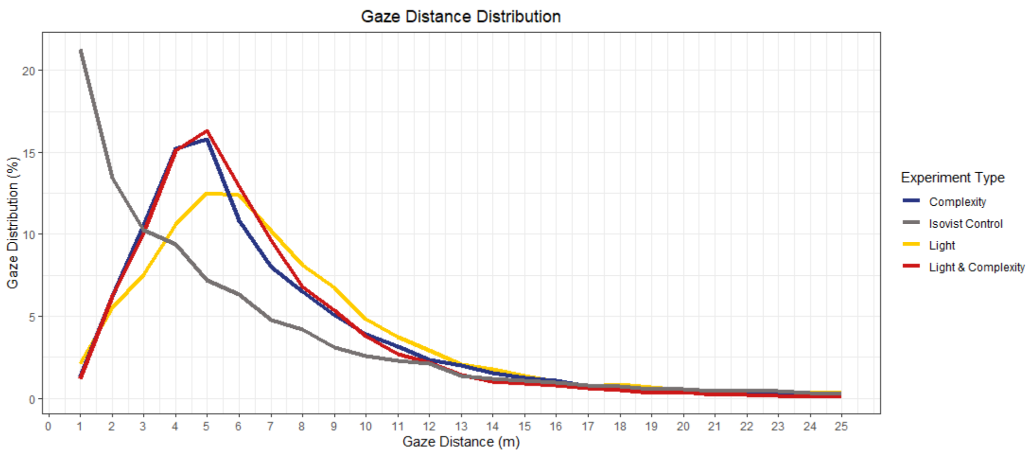

Figure 6 Gaze distance across each experiment compared to an isovist control, which was placed at 1000 random points in each map with sampling rays at 10-degree increments to estimate the gaze distance distribution and the mean gaze distance across all maps of 6.45m

Notably, the collected data is intriguing due to the distinct gaze behaviour exhibited in the lighting experiment, which differed from the 'complexity' and 'lighting & complexity' experiments. As complexity variation was not present in the light experiment, it is reasonable to hypothesise that the manipulation of complexity had more of an impact on participants' gaze-distance behaviour than lighting. This might suggest that the varying complexity levels within the environment are more likely to divert participant's attention away from the more 'search optimal' gaze depth observed in the lighting-only experiment.

This data can be interrogated further through an inspection of the effects of the individual variable levels upon the gaze distance behaviour in each experiment (**Figure 7**). Within the lighting experiment there is a much clearer correlation between the light level and gaze distance, wherein participants displayed a consistently greater mean gaze distance the better lit the environment, as demonstrated by the correlation between gaze distance and light level. This agrees with the results in the previous section, in which increased light coincides with increased route selection based on visible distance, thus suggesting that greater light draws the eye. Suggesting that participants would demonstrate more optimal search behaviour in better lit conditions. In the complexity experiment, the mean gaze distances by levels suggest no distinct correlation between gaze distance and complexity level. When considered in conjunction with the route selection data, this might suggest that complexity choice is unrelated to gaze distance behaviour.

Level	*Mean Gaze Distance (Light)*	*Mean Gaze Distance (Complexity)*
0	6.42m	7.04m
1	7.19m	6.85m
2	7.32m	5.58m
3	8.23m	6.99m

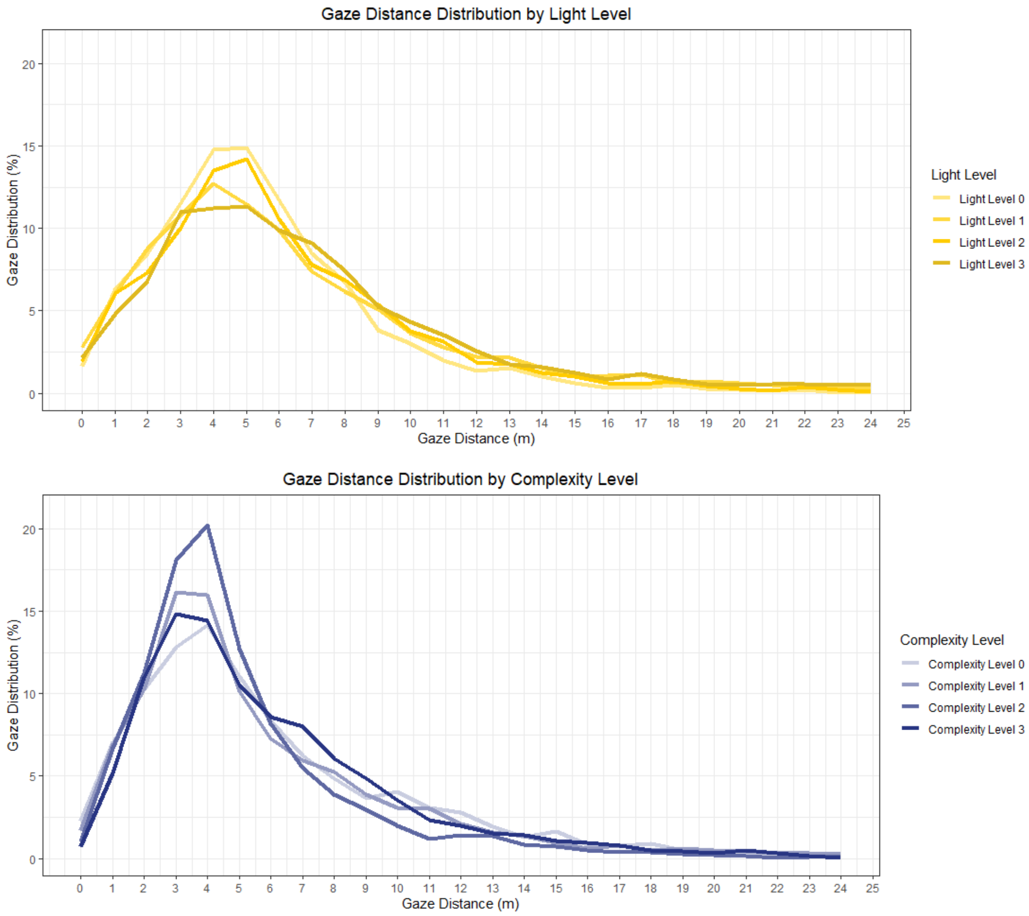

Figure 7 Gaze distance distribution across each condition level in the lighting-only (yellow) and complexity-only (blue) experiments

The nature of the gaze data across participants was also assessed through the distribution of time spent considering the choice variable, comparatively to the options presented to the participant at each choice. This was done to test the hypothesis that the time spent looking at a choose would affect the decision made. To ensure the validity of the data, a data confidence value was calculated. Where data accuracy was below 70%, the data was omitted from the distribution calculation. This was calculated by assessing the difference in the quantity of positional and gaze data, resulting from the omission of data from the eye-tracking headset when gaze confidence readings were lower than 90%. Here, it was found the that the choice gaze-distribution correlates across all experiment conditions (**Figure 8**). With participants tending to look at their choice for average of 65.25% of the time at *junctions* across 983 samples with a standard deviation of 28.83%, and an average of 53.93% of the time at *intersections* across 579 samples with a standard deviation of 27.35%.

Choice Type	*Expected % of Gaze Upon Choice*	*Observed % of Gaze Upon Choice*
Junctions	50%	65.25%
Intersections	33.33%	53.93%

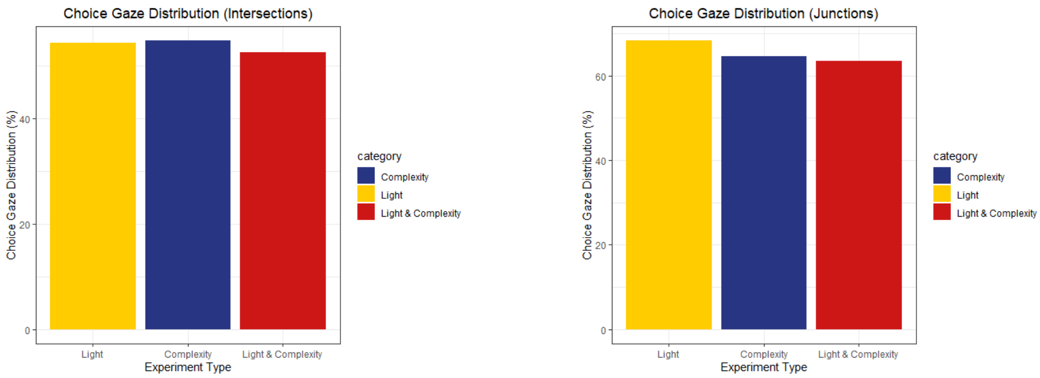

Figure 8 Mean participant gaze distribution percentage upon the chosen option for intersections (left) and junctions (right) across all participants for the light, complexity, and light & complexity experiments

As this observed mean differs from the expected means presented in alternative hypothesis, which would indicate an expected equal distribution of 33.3% for intersections and 50% for junctions if participants were to consider each option equally before deciding. This might suggest that the time spent looking at an option does correlate with the choice.

However, as the gaze distribution is not changing across the differing non-spatial variables, this implies that while we look at our choice for longer, this a factor is independent of effect of the various low-level visual features. This suggests that, despite participants showing a preference for either more complex or well-lit options, they evaluate each turning option independently of the low-level visual cues. Considering the data in **Figure 7**, it appears that while the gaze may be affected by light overall, it doesn't play a role when making a choice. It is also important to consider the practical difference between the choice mean and expected mean, as the large standard deviation of the data further implies that other factors affected this distribution.

This observation is further supported by **Figure 9**. Which indicates the percentage distribution of the gaze across the different conditions of light and visual complexity are roughly equal. Further implying that while the time spent looking at a condition correlated with the selection process, this was also independent of the low-level visual cues.

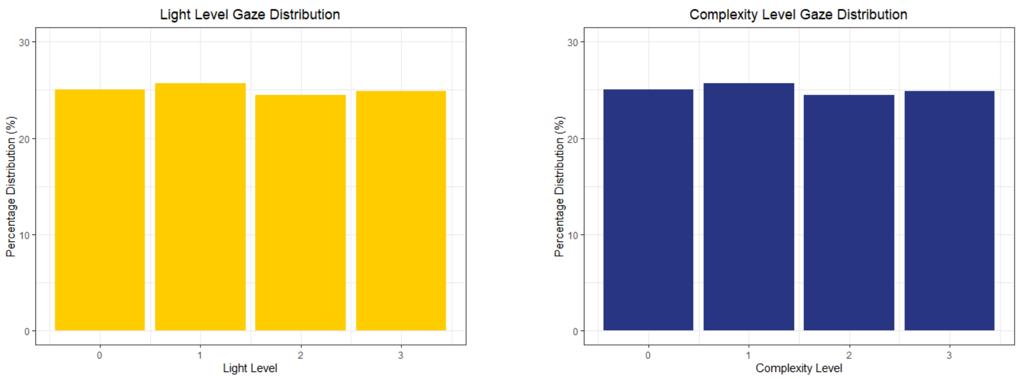

Figure 9 Normalised gaze distribution across each light (left) and complexity (right) levels while making choices at junctions/intersections in the lighting experiment and complexity experiment respectively.

5 CONCLUSION

5.1 Re-evaluating the role of low-level cognition in navigation.

These results suggest that low-level visual cues have an impact on decision making and higher-level cognitive processes. Implying that low-level cognitive processes, such as the signal intensities of our environment, provide the necessary perceptual information required for higher-level cognitive processes, such as decision-making, to occur. High-level processes, contrastingly, might evaluate and integrate this lower-level perceptual information to make an informed decision, based upon the overall goal. This in turn, is supported by theories that visual attention isn't necessarily tied to the physical eye movements, but rather an internal cognitive mechanism (Posner, 2012), and the idea that the effect of these low-level cues are a pre-attentive process (Treisman, 1986). Thus, highlighting the importance of the visual saliency and impact of these cues at the lower level, in that they bare weight the decision-making process despite not necessarily baring an impact on the attentive nature of the eye's fixations.

These findings therefore highlight the importance of exploring the impact of these non-spatial cues upon human behaviour and the complex interplay of low and high-level cognitive processes in navigation and decision-making. Utilising both approaches provides a more complete understanding of navigational behaviour from the lowest through the highest cognitive levels.

From this data, we can infer that these low-level visual cues do have an impact on navigational behaviour, supporting the hypothesis. The variables of angle and visible distance, which have been seen to influence movement in existing cities and spaces in which these are highly varied, appear to have little effect in the case of this data from a controlled, orthogonal environment. However light and complexity, when varied, do appear to have an effect on decision-making and movement through space. The gaze is also affected by these non-spatial variables overall, particularly by light, but not when deliberating at junctions and intersections. Thus, suggesting that this may not be through immediate visual attention, rather an indirect mechanism. This is further supported by data in **Figure 8** and **Figure 9**, which demonstrates that while participants might have spent more time fixating upon their choice when making decisions, this was unaffected by the differing levels of light and visual complexity.

This research into the impact of non-spatial low-level visual cues on navigation thus provides a valuable insight into the basic cognitive and perceptual processes that underlie navigational behaviour in humans, ultimately suggesting these variables can be individually meaningful and bare significance over the way we interpret and respond to our environment.

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