

Evidence from London taxi drivers of hierarchical route planning in a real-world environment

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I, Eva-Maria Griesbauer, hereby confirm that the work presented in this thesis is my own. Further, I confirm that where information has been derived from other sources, it has been indicated in the work.

ABSTRACT

The ability to navigate a spatial environment strongly depends on how well individuals learn, represent and make use of their knowledge about the environment. In the past, research investigated these aspects separately and often in a virtual environment. The current work studied these three aspects of navigation in a real-world setting to understand how humans navigate naturally in a complex, urban environment like London, UK. Of particular interest was to determine if there was evidence of hierarchical representations during route planning as found in previous behavioural, neuroscientific or computational studies. Most past studies have explored knowledge for simplistic environments or fragmented knowledge of real-world environments. By contrast, licensed London taxi drivers acquire a unique, almost perfect mental representation of the street network, the location of places and the traffic rules that apply to it. Here, the rare knowledge of these navigation experts was explored in three studies with novel approaches. First, to gain an understanding of the training process of unqualified taxi drivers, information from an interview with a teacher, training lessons and study material was collected, summarised and reported. A range of learning strategies was identified that was linked to theoretical, map-based learning and practical, in-situ experiences of London and pointed towards a segmented planning of routes through subgoal selection. Second, a potential mental segregation of London was studied with qualified taxi drivers through boundary drawings of specific London districts with a paper map to understand a potential hierarchical representation. Higher agreement was found for geographical structures and topically distinct districts surrounded by a linear, almost rectangular street network, whereas agreement was lowest for irregularly shaped districts with similarities to neighbouring areas. Finally, taxi drivers were asked to plan and then verbally recall each street they would take along routes between selected origin destination pairs. Audio recordings of these routes made it possible to relate the response times between individual streets to specific street network properties. The analysis using a linear mixed model indicated slower responses at upcoming turns and entering main roads, whereas boundary streets were recalled faster, as were final streets when compared to initial street. No effects of Euclidean distance or detours were found. Observations from the training process indicate that a potential segregation of the environment, which might impact on later route planning, might be formed already through specific learning strategies. Faster response times for boundary streets support models in which planning is hierarchical.

These findings extend past work on route planning in lab-based networks to real-world city street networks and highlight avenues for future research to explore and make use of real-world data.

IMPACT STATEMENT

Results and ideas from this research project contribute vital insight on how individuals learn, represent and exploit their knowledge of complex urban spaces. Academically, this insight can be beneficial for a variety of areas of research, including, but not limited to psychology, neuroscience, geoscience and computational modelling. In particular, spatial cognition, behavioural neuroscience, urban planning and hierarchical modelling are strongly linked to this ecologically valid project, which also has the potential to motivate and encourage future research projects to be moved from a strongly controlled laboratory setting to a real-world environment.

Apart from academic research, this project could impact areas of urban planning, spatial navigation, policy design, industrial research, clinical research, public health and quality of life. Specifically, ideas and findings from this project can be used to improve navigation aids, traffic control, or cartographic designs. A better understanding of how humans represent and use spatial information can impact the quality of life of individuals, especially for those with deteriorating navigation abilities, or with underlying clinical conditions, such as dementia patients.

STATEMENT OF CONTRIBUTION

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Verbal data from taxi drivers on route planning tasks was collected and transcribed by a group of undergraduate and graduate UCL students as part of their course work and final year projects under the supervision of Prof Hugo Spiers. This group of students included for the first set of data collection Emily Hoy, Layla Massoud, Florence Stow, Agnese Merlo, Lea Evers, and for the second set of data collection Ishita Aradhey, Ola Volhin, Dalton Barham and Elahi Hossain.

Several collaborators provided data visualisations, which were adapted for figures of this work as indicated in captions. These collaborators were Professor Ed Manley (**Figure 2.5, Figure 4.4**), Gabriele Filomena (**Figure 3.1**) and Melda Salhab (**Figure 3.3, Figure 3.4**). Visuals and photos of learning material from the Knowledge Point School were adapted for used in **Figure 2.2, Figure 2.3, Figure 2.4** and **Figure 2.6**. Consent for adapted use was provided by the Taxi Trade Promotions, Knowledge Point School Ltd, Brewery Road, London, UK, and individuals interviewed or depicted in pictures.

Additionally, geographical data of Euclidean and path distances to the destination in **Chapter 4** was supplied by Professor Ed Manley.

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1. GENERAL INTRODUCTION

Navigation, “the skill or the process of planning a route for a ship or other vehicle and taking it there” ([Oxford Learner’s Dictionary](#), n.d.), enables humans to travel between places by forming and executing travel plans, according to this definition. The term ‘navigation’, from the Latin word *navigare*, *navis* for ‘ship’ and *agere* for ‘to drive’ ([Oxford Learner’s Dictionary](#), n.d.), was originally limited to maritime travel, but has now also become an established expression in land, aeronautic and space travel. In behavioural science it is now used as an umbrella term for various actions that enable and are central to navigation. These include the formation of spatial memory (e.g. [Dahmani & Bohbot, 2020](#), [Hejtmánek, Oravcová, Motýl, Horáček & Fajnerová, 2018](#)), processing of spatial information (e.g. [Münzer, Zimmer, Schwalm, Baus & Aslan, 2006](#); [Münzer, Zimmer & Baus, 2012](#)), selection of navigation strategies (e.g. [Wiener, Schnee & Mallot, 2004](#)), self-orientation and localisation of places (e.g. [Barry & Burgess 2014](#)), the efficient use of maps and other navigation aids (e.g. [Hejtmánek, Oravcová, Motýl, Horáček & Fajnerová, 2018](#); [Gardony, Grunyé, Mahoney & Taylor, 2013](#)), the planning of routes (e.g. [Wiener & Mallot, 2009](#)) and the execution of route plans ([Hölscher, Tenbrink & Wiener, 2011](#)).

On a daily basis, humans rely on these aspects of navigation to go for walks, bike rides and on sightseeing trips, to identify their location, flexibly structure the visit of multiple places (e.g. from home, to a coffee shop, the supermarket, the gym, a friend’s place and back home), or just to find the correct room on the right floor in a hospital or company. Often these actions are carried out without much effort in a familiar environment, but can become challenging in a large, complex or unfamiliar environment. However, chances of losing orientation and getting lost in such an environment are nowadays decreased as a result of Global Positioning Systems (GPS) and navigation aids that reliably guide individuals to their destinations (e.g. [Dahmani & Bohbot, 2020](#), [Hejtmánek, Oravcová, Motýl, Horáček & Fajnerová, 2018](#); [Gardony, Grunyé, Mahoney & Taylor, 2013](#)). Even though these guided-navigation devices appear like a great technological innovation in a constantly growing urban environment with a fast-paced life style that requires individuals to act time efficiently, they come with an enormous drawback for regular GPS-users: Instruction-based devices have been found to impair spatial awareness and navigation performance ([McKinlay, 2016](#), [Münzer, Zimmer, Schwalm, Baus & Aslan,](#)

[2006](#)) as they prevent humans from relating to the environment to process spatial information and creating spatial memories ([Münzer, Zimmer, Schwalm, Baus & Aslan, 2006](#), [Ishikawa, Fujiwara, Imai & Okabe, 2008](#), [Münzer, Zimmer & Baus, 2012](#)). Ultimately, this lack of spatial training in the long run causes humans to experience even more often the difficulties they wanted to avoid in the short run.

An evolutionary point of view

It is interesting to note how easily human navigation abilities are impacted by the navigation methods that individuals use and are in danger of rapidly deteriorating if left untrained. In modern, technologically advanced societies instruction-based navigation aids have only become widely available within the last two decades, but they have already left a negative impact on individuals' navigation abilities (e.g. [McKinlay, 2016](#), [Münzer, Zimmer, Schwalm, Baus & Aslan, 2006](#)). However, from an evolutionary point of view, it took millennia for these skills to evolve. Initially, it was the ability to remember food sources, places of safety and territorial boundaries that was vital for the survival of individuals, families, tribes and ultimately the human species. Only those survived, who managed to develop and exploit these skills efficiently and ultimately passed on innate ability and knowledge from generation to generation. Native tribes, such as the Puluwat ([Gladwin, 2009](#); [Ekstrom, Spiers, Bohbot & Rosenbaum, 2018](#)) or Aboriginal Australians (e.g. [Norris & Harney, 2014](#)), are examples of such exceptional navigators who still train and use their navigation ability to travel enormous distances with great precision.

In the animal world, the survival of most species still strongly depends on their navigation abilities. Finding or returning to food sources and places of nesting and reproduction are innate predispositions. Specifically, foraging and territorial behaviours in primates ([Ofstedal, 1991](#); [Janson & Goldsmith, 1995](#)) ensure access to and availability of appropriate food resources. Turtles (e.g. [Nichols, Resendiz, Seminoff & Resendiz, 2000](#); [Luschi, Papi, Liew, Chan & Bonadonna, 1996](#); [Koch, Carr & Ehrenfeld, 1969](#)), salmon (e.g. [Thorpe, 1988](#); [Hansen, Jonsson & Jonsson, 1993](#); [Bottom, Jones, Cornwell, Gray, & Simenstad, 2005](#)) or sharks ([Gore, Rowat, Hall, Gell & Ormond, 2008](#); [Weng, Foley, Ganong, Perle, Shillinger, & Block, 2008](#)) cover enormous distances, sometimes up to several thousand kilometres (e.g. [Gore, Rowat, Hall, Gell & Ormond, 2008](#)) to nest and reproduce at specific places that were genetically imprinted at their birth (e.g. [Thorpe, 1988](#)). During early life, these animals learn cues that help them later with their *homing*

(i.e. the animals ability to return to their home territory) and *migration* (i.e. seasonal travelling of animals between regions) as they learn to rely on external cues, such as streams, tidal currents, freshwater flow, or chemical compositions in the water ([Hansen, Jonsson & Jonsson, 1993](#), [Bottom, Jones, Cornwell, Gray, & Simenstad, 2005](#)) to find the location of their origins. Similarly, birds like pigeons (e.g. [Wallraff & Wallraff, 2005](#); [Walcott, 1996](#)) exploit the geomagnetic field and solar or stellar cues, as well as their innate sense of direction ([Wallraff & Wallraff, 2005](#); [Walcott, 1996](#); [Beason, Wiltschko & Wiltschko, 1997](#)) to return to their nesting territories. However, this ability to navigate extreme distances is not unique to highly developed species. Even invertebrates, such as butterflies (e.g. [Reppert, Gegear & Merlin, 2010](#); [Zhan, Merlin, Boore & Reppert, 2011](#)), ants (e.g. [Franks & Fletcher, 1983](#); [Wilson, 1958](#); [Wilson, 1971](#)) and bees (e.g. [Menzel, Geiger, Chittka, Joerges, Kunze & Muller, 1996](#); [Dyer & Could, 1983](#)) display homing and migration strategies similar to mammals, reptiles, fish and birds, highlighting the evolutionary importance of efficient navigation abilities for survival across species.

Evidence for Mental Representations of Spaces

Evidence from migrating and homing animals highlights ways in which external cues are used to find a specific place in an environment. However, if external cues only trigger animals to repeatedly use an initially learnt, successful route to a destination, such as a particular path to a food source, their navigation abilities could be simply explainable through stimulus-response learning. Reaching a destination (e.g. a food source or nesting location) would then create a positive experience that increases the likelihood of the animal repeating the previous action in relation to the presence of a cue (i.e. following the same actions to external cues to take the same route), and decreases the likelihood of displaying alternative actions with respect to that cue that would lead to a different outcome (e.g. as a different route). However, such stimulus-response learning would fail to explain flexible adaptations of animal behaviour in situations where for instance the usual path to a food source is blocked and a detour is required. Such efficient adaptations in behaviour would rely on additional information about the spatial layout of the environment that, in combination with external cues, would enable animals to find an alternative route.

[Tolman \(1948\)](#) provided experimental evidence for such efficient adaptations of rats at blocked paths in a familiar maze environment and argued for the existence of a

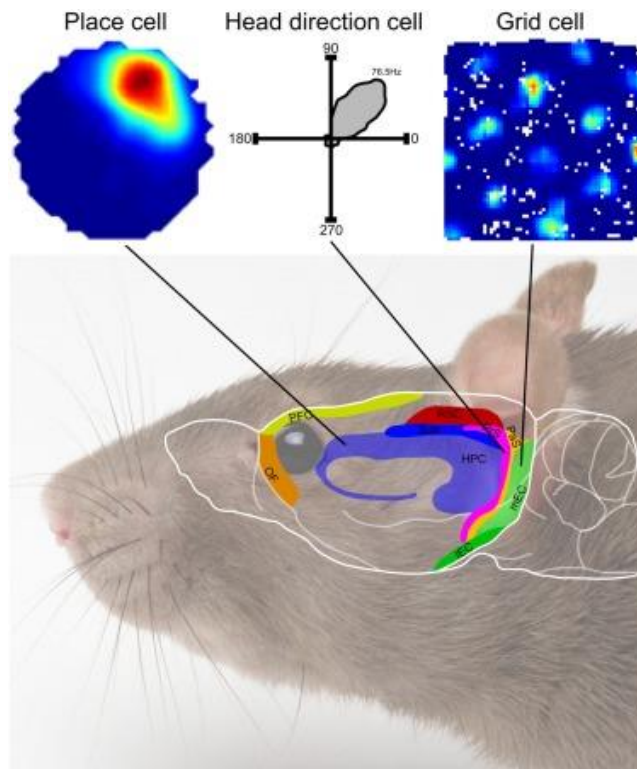


Figure 1.1. Place, grid and head direction cells. Anatomical representation of navigation relevant cells in the rat brain. Place cells (left), in the hippocampus, code a specific area in a space. Head directions cells (middle) activate to indicate a specific facing direction. Grid cells (right) code location, distance and direction information between places. Adapted from: [Grieves & Jeffery, 2017](#).

cognitive map, i.e. a mental map-like representation of the environment. Only enough familiarity with the maze environment could create a mental representation of the maze, that rats would be able to exploit for shortcut-taking to find a food source. Further, recent evidence for the existence of cognitive maps has come from the tracking of free-ranging bats, exhibiting effective goal-directed foraging behaviour. Computational simulations strongly supported the exploitation of information about the spatial layout the bats were foraging in ([Toledo, Shohami, Schiffner, Lourie, Orchan, Bartan & Nathan, 2020](#)).

On a neural level, the cognitive maps theory was supported by the discovery of *place cells*, which are cell formations in the hippocampus that display place-sensitive firing patterns ([O'Keefe & Dostrovsky, 1971](#); [O'Keefe and Nadel, 1978](#)). Different cell groups were found to activate at specific areas, the so-called *place fields*, of an environment and allow to distinguish between places, thus creating a neural representation of the real-world environment in form of a mental mapping (**Figure 1.1**, left). Furthermore, lesions to the hippocampus prevented rats from efficient place-related navigation ([Morris, Garrud, Rawlins & O'Keefe, 1982](#)). However, place cells mainly carry place-related information and their mapping pattern for an environment is random and completely independent from the mapping pattern in another, similar environment or the same environment under a

different context ([Morris, Garrud, Rawlins & O’Keefe, 1982](#)). Information on location, distance and direction are mainly coded in neural cells of the entorhinal cortex, the *grid cells* ([Hafting, Fyhn, Molden, Moser & Moser, 2005](#)). These cells, similar to place cells, indicate the location of places of the environment, but in contrast to place cells, are not limited to one location alone as they activate in regular, hexagonal, grid-like patterns across the environment (**Figure 1.1**, right). Additional information of directional input is coded through *head direction cells* ([Taube, Muller & Ranck, 1990](#)), which activate in dependence of facing in a preferred firing direction and are distributed across several cortical (e.g. [Chen, Lin, Green, Barnes & McNaughton, 1994](#); [Giocomo, Stensola, Bonnevie, Cauter, Moser & Moser, 2014](#)) and subcortical (e.g. [Taube, 1995](#)) regions of the brain (**Figure 1.1**, middle).

In humans, supporting evidence for the existence of place cells ([Las & Ulanovsky, 2014](#); [Ekstrom, Kahana, Caplan, Fields, Isham, Newman & Fried, 2003](#); [Doeller, Barry & Burgess, 2010](#)), grid cells ([Doeller, Barry & Burgess, 2010](#); [Constantinescu, O’Reilly & Behrens, 2016](#); [Jacobs, Weidemann, Miller, Solway, Burke, Wei, Suthana, Sperling, Sharan, Fried & Kahana, 2013](#)) and head direction cells ([Baumann, & Mattingley, 2010](#); [Marchette, Vass, Ryan, & Epstein, 2014](#); [Shine, Valdés-Herrera, Hegarty, & Wolbers, 2016](#)) has also been found. Studies with London taxi drivers specifically identified the hippocampus to play a central role in human spatial navigation ([Maguire, Frackowiak & Frith, 1997](#); [Maguire, Gadian, Johnsrude, Good, Ashburner, Frackowiak & Frith, 2000](#); [Woollett & Maguire, 2009](#); [Woollett & Maguire, 2011](#); [Maguire, Nannery & Spiers, 2006](#); [Woollett & Maguire, 2012](#); [Spiers & Maguire, 2006](#); [Spiers & Maguire, 2008](#); [Maguire, Spiers, Good, Hartley, Frackowiak & Burgess, 2003](#); [Woollett, Spiers & Maguire, 2009](#)).

As these cells work together to provide and process navigation relevant information, the brain is ultimately able to store this rich information about specific locations, distances and relative locations of places as well as directional information to build a cognitive map. In the following chapters, such a cognitive map will be studied in a broader sense from a behavioural point of view to understand how individuals build, represent and exploit spatial information in a complex, real-world environment like London, UK. Here, the cognitive map refers to the mental representation that individuals gain of the street network, places located in it and spatial properties that structure this environment and potentially impact not only their representation, but also the route planning behaviour based on this mental representation.

Evidence from Behavioural Studies

Learning spatial information about a real-world environment, relations between places and the layout with respect to cardinal directions can involve processing various sources of information. Theoretical knowledge about spaces can be obtained from studying and memorising maps (e.g. [Münzer, Zimmer, Schwalm, Baus & Aslan, 2006](#); [Münzer, Zimmer & Baus, 2012](#); [Coutrot, Patai, Silva, Manley, Weiner, Dalton, Hölscher, Hornberger & Spiers, 2019](#);), through verbal descriptions or instructions from GPS systems (e.g. [Ishikawa, Fujiwara, Imai & Okabe, 2008](#)) or in conversations with other individuals with spatial knowledge (e.g. [Hölscher, Tenbrink & Wiener, 2011](#)). Maps provide precise, extensive geographical information on distances, directions and relations between places and their connection with each other through a street network. In contrast, individuals might highlight and focus on specifically relevant information, such as landmarks or traffic routes, that carry importance in a specific situation and might not be obvious from map studies alone. More efficient than theoretical processing of spatial information is active interaction with the environment (e.g. [Dahmani & Bohbot, 2020](#), [Hejtmánek, Oravcová, Motýl, Horáček & Fajnerová, 2018](#)) that forces individuals to explore, engage and memorise their environment in pursuit of a goal.

From a behavioural perspective, studies on spatial learning have mainly focused on specific aspects and contexts, including education (e.g. [Montello, Grossner & Janelle, 2014](#)), the relation to sensory input and an aging population (e.g. [Wiener, Carroll, Moeller, Bibi, Ivanova, Allen, & Wolbers, 2019](#); [Hartmeyer, Grzeschik, Wolbers & Wiener, 2017](#); [König, S. U., Schumann, F., Keyser, J., Goeke, C., Krause, C., Wache, S., Lytochkin, A., Ebert, M., Brunsch, V., Wahn, B., Kaspar, K., Nagel, S. K., Meilinger, T., Buelthoff, H., Wolbers, T., Buechel, C., & Koenig, P., 2016](#)), environmental cues (e.g. [Gillner & Mallot, 2006](#); [Franz, Schölkopf, Mallot & Buelthoff, 1998](#)), contextual learning (e.g. [Howard, Howard, Dennis, Yankovich & Vaidya, 2004](#); [Howard, Fotedar, Datey & Hasselmo, 2005](#)) or map-design and cartography (e.g. [Montello, 2013](#); [Montello, 2010](#); [Battersby & Montello, 2009](#)).

However, experiences might be prone to mental misrepresentations of spatial layouts as sensory detectability, perception and memory of spaces often lack precision and impact detailed information processing. Ultimately, these might lead to perceptual biases and conceptual distortions of entire spaces. For instance, distances between places have been underestimated when places belonged to the same region and overestimated, if they were

separated by regional boundaries (e.g. [Okabayashi & Glynn, 1984](#); [Thorndyke, 1981](#)). Distortion effects often also result in rotation and alignment effects (e.g. [Tversky, 1981](#); [Tversky 1992](#)) as well as simplification (e.g. [Okabayashi & Glynn, 1984](#); [Stevens & Coupe, 1978](#)) of spatial layouts, such as a west-east generalisation of the River Thames in London (UK) that ignore riverbends and focus on a more linear layout. Spatial and temporal distortions detected during mental walks point towards cognitive biases during route recall (e.g. [Brunec, Javadi, Zisch & Spiers, 2017](#); [Jafarpour & Spiers, 2017](#)). On a small scale, turns were found to impact memory recall of places and landmarks along routes ([Brunec, Ozubko, Ander, Guo, Moscovitch, & Barense, 2020](#)). Boundaries, as well as other perceptual spatial structures, such as neighbourhoods, districts, edges and bottlenecks (e.g. [Lynch, 1960](#)), can impact how humans mentally represent and use their representation of urban spaces for planning behaviour. Instead of an entire map that would support profound route knowledge, a simplification towards a labelled, metric network of cognitive graphs, have also been discussed as possible representations (e.g. [Chrastil & Warren, 2014](#)). Even though these can also well explain distance distortions, cognitive graphs alone are not enough to enable humans to plan routes as specific topological knowledge about the street network is not represented. However, humans might rely on cognitive graphs at early stages of the development of their cognitive map, or even use these for cores planning, before specific steps are filled at later stages (e.g. [Wiener, Ehbauer & Mallot, 2009](#)).

Route planning, and in particular such hierarchically organised planning structures, have become a focus in behavioural psychology (e.g. [Wiener & Mallot, 2003](#)), as well as computational modelling (e.g. [McNamee, Wolpert & Lengyel, 2016](#)). Several findings indicate that humans use a regionalised representation of the environment for route plans (e.g. [Wiener & Mallot, 2003](#); [Wiener, Schnee, Mallot, 2004](#); [Wiener, Ehbauer & Mallot, 2009](#); [Balaguer, Spiers, Hassabis & Summerfield, 2016](#); [Schick, Halfmann, Hardiess, Hamm & Mallot, 2019](#)). Additionally, computational models highlight a better efficiency of hierarchical representations over flat representations that do not regionalise the environment (e.g. [McNamee, Wolpert & Lengyel, 2016](#); [Pezzulo, Rigoli & Friston, 2018](#)). Examples of non-hierarchical representations include tree-search algorithms, that consecutively explore different series of actions until a solution is found without systematically eliminating options (e.g. [Elliott & Lesk, 1982](#); [Miller & Venditto, 2020](#)). In contrast to these representations, where all locations are considered equally, representations that involve a regionalisation reduce the number of options to relevant

regions and allow to focus the planning behaviour on a selected subset of options (e.g. [McNamee, Wolpert & Lengyel, 2016](#); [Pezzulo, Rigoli & Friston, 2018](#)). However, most behavioural evidence stems from a highly controlled, artificial environments using a virtual reality, rather than real-world settings (e.g. [Wiener & Mallot, 2003](#); [Wiener, Schnee, Mallot, 2004](#); [Wiener, Ehbauer & Mallot, 2009](#); [Balaguer, Spiers, Hassabis & Summerfield, 2016](#); [Schick, Halfmann, Hardiess, Hamm & Mallot, 2019](#)). It still remains open, how humans can efficiently learn spatial knowledge to build a mental representation of their environment, i.e. a cognitive map, and use this map for route planning purposes.

In the following, three studies explore will address these questions. The first study will focus on, how a group of expert navigators, London taxi drivers, acquire their knowledge of locations, places, streets and traffic rules in order to navigation freely, flexibly and without relying on physical maps or GPS systems. Verbal reports, interviews and study material from a knowledge taxi school, as well as official, publicly available regulations from Transport for London (TfL) have been collected, systematically analysed and reported. In a second study, qualified London taxi drivers reported perceptual street-network boundaries for London districts. These perceptual boundaries were ultimately used to test if route planning in a separate group of taxi drivers relied on a hierarchical representation of London (UK). Past research on these navigation experts will be reviewed in detail in the next chapter.

2. HOW LONDON TAXI DRIVERS BUILD THEIR COGNITIVE MAP FROM 26,000 STREETS OF THE ‘KNOWLEDGE OF LONDON’

2.1. Abstract

Licensed London taxi drivers are unique navigators, who rely on their own navigation abilities to flexibly plan routes through a complex, urban space without assistance on physical maps or GPS devices. This ability is a result of years of training during their qualification process, that ultimately even causes neural changes in their hippocampus. Here, a structured overview of their training process is recorded and analysed, including their learning material, learning strategies, practical applications and examination process. These observations could impact on spatial learning methods and provide insight on how experts mentally represent a real-world environment.

2.2. Introduction

The ability to navigate an environment depends strongly on the knowledge of that environment. This knowledge can be gained in multiple ways, for instance, by following instructions on GPS devices, memorising a map, or through exploration. Over the last decades, there has been increasing interest in studying spatial learning to understand how these methods differ and impact the acquisition of spatial memory in a virtual environment, small-scale real-world environment, or in a graph network (e.g. [Dahmani & Bohbot, 2020](#), [Hejtmánek, Oravcová, Motýl, Horáček & Fajnerová, 2018](#); [Gardony, Grunyé, Mahoney & Taylor, 2013](#); [Münzer, Zimmer & Baus, 2012](#); [Ishikawa, Fujiwara, Imai & Okabe, 2008](#); [Münzer, Zimmer, Schwalm, Baus & Aslan, 2006](#); [Siegel, & White, 1975](#); [Streeter & Vitello, 1986](#), [Balaguer, Spiers, Hassabis & Summerfield, 2016](#)). Even though GPS devices are the preferred method of navigation ([McKinlay, 2016](#)), evidence strongly suggests that the increased use of GPS devices leads to a decline in spatial memory over time ([Dahmani & Bohbot, 2020](#)) as it is mainly associated with habitual learning of a particular route ([Münzer, Zimmer, Schwalm, Baus & Aslan, 2006](#)). In contrast to GPS- and instruction-guided navigation, map-based navigation was found to support spatial learning, knowledge acquisition of the environment and enhance navigation performance when individuals are required to navigate without any navigation aids (e.g. [Ishikawa, Fujiwara, Imai & Okabe, 2008](#); [Münzer, Zimmer & Baus, 2012](#); [Münzer, Zimmer, Schwalm, Baus & Aslan, 2006](#)). In this context, neuroscientific

research has found the hippocampus to be key to storing spatial representations of the environment in form of cognitive maps (e.g. [O'Keefe & Dostrovsky, 1971](#); [O'Keefe & Conway, 1978](#); [O'Keefe & Nadel, 1978](#); [Tolman, 1948](#); [Shapiro, 2015](#)). This in turn facilitates spatial navigation even in a large-scale, complex, real-world environment like London (UK), where a detailed spatial representation is vital for travelling to a destination ([Maguire, Nannery & Spiers, 2006](#)).

Acquiring this type of knowledge is central to the training of licensed London taxi drivers, who possess a remarkable and unique knowledge of the London (UK) street network and have become coveted subjects for studies. In contrast to the general population, London taxi drivers are able to mentally plan routes across an environment that contains more than 26,000 streets within the six-mile area around Charing Cross, which is considered the geographic centre of London ([A to Z from Collins The Knowledge, 2020](#)). Additionally, taxi drivers have sufficient knowledge to also navigate main artery roads in the suburbs, an area that covers about 60,000 roads within the circular M25 ([The London Taxi Experience - The Knowledge, 2020](#); numbers may vary depending on sources, road types and the definition of the boundary of London). Taxi drivers accomplish this without relying on physical maps or navigation aids.

In the past, this skill has been studied through a series of brain imaging studies that provide evidence of structural changes in the hippocampus of licensed London taxi drivers as a result of spatial knowledge acquisition and use (e.g. [Maguire, Frackowiak & Frith, 1997](#); [Maguire, Gadian, Johnsrude, Good, Ashburner, Frackowiak & Frith, 2000](#); [Woollett & Maguire, 2009](#); [Woollett & Maguire, 2011](#); [Maguire, Nannery & Spiers, 2006](#); [Woollett & Maguire, 2012](#); [Spiers & Maguire, 2008](#); [Maguire, Spiers, Good, Hartley, Frackowiak & Burgess, 2003](#); [Woollett, Spiers & Maguire, 2009](#); [Smith, 2011](#)). In particular, an increase in the posterior hippocampus was closely related to learning the knowledge of London during the qualification phase of taxi drivers ([Woollett & Maguire, 2011](#)) and the number of years driving a taxi (post qualification), where this knowledge is actively applied on a daily basis as part of their job ([Maguire, Gadian, Johnsrude, Good, Ashburner, Frackowiak & Frith, 2000](#); [Maguire, Nannery & Spiers, 2006](#)). However, acquiring the knowledge of London seems to come at a cost of learning and retaining new visuo-spatial information, which co-occurs with a concurrent volume decrease in the anterior hippocampus ([Maguire, Nannery & Spiers, 2006](#); [Woollett & Maguire, 2009](#); [Woollett & Maguire, 2012](#)).

Despite this extensive number of studies, that has been carried out to provide important insight on the effects of learning, retaining and using spatial knowledge on hippocampal structure, hardly any attention has been paid to the methods that taxi driver students use to learn this vast amount of knowledge ([Skok, 1999](#)). Neither has there been a link to hippocampus-related learning and study designs that rely on spatial learning. However, a better understanding of how spatial learning impacts the hippocampus, the brain area that is also affected by Alzheimer's (e.g. [Coughlan, Coutrot, Khondoker, Minihane, Spiers, & Hornberger, 2019](#); [Kunz, Schröder, Lee, Montag, Lachmann, Sariyska, Reuter, Stirnberg, Stocker, Messing-Floeter, Fell, Doeller, & Axmacher, 2015](#)), can have central implications for prospective human navigation and the designs and applications of navigation aids in the future. This project aims to provide a structured report of this learning process, the underlying motives to study it, and the methods and techniques involved.

2.3. Methods

In order to obtain a holistic understanding of the learning process of taxi drivers, different types of sources of information have been consulted. These sources included a semi-structured interview (ethics approval was obtained under the ethics number CPB/2013/150) with a teacher from a London knowledge school (here referred to as K.T. for '*Knowledge Teacher*'), an email exchange with Robert Lordan, the author of '*The Knowledge: Train Your Brain Like A London Cabbie*' ([Lordan, 2018](#)), an open introductory class of the Knowledge of London, regular scheduled classes for current students, school specific study material and online information from the TfL ([Learn the Knowledge of London, Transport for London, n.d.](#); [Electronic blue book, 2019](#)).

The interview with the knowledge school teacher was audio-recorded and transcribed. Relevant passages of the interview can be found in **Appendix A**. The teacher gave written consent for the content of this interview to be cited and published. The additional information was collected during attendances of knowledge school training classes, including an introductory class and several classes with more advanced students.

The information collected from these sources was systematically summarised and is reported in the following.

2.4. Observations

Taxi drivers in London have to demonstrate a thorough *Knowledge of London* within the six-mile radius originating at Charing Cross (see **Figure 2.1a**) to earn the green badge that qualifies them to drive a black cab ([Electronic blue book, 2019](#)). Within this area, taxi drivers are expected to be able to plan the shortest routes (*'runs'*) between any two potential places (*'points'*) their customers might want to travel to or from, and name all roads or streets that are part of that run in the correct, sequential order, including turning instructions.

Historically, the exact roots of the knowledge are unclear as written evidence is mostly missing. The first licenses and regulations for horse-driven carriages date back to the early 1600s by Oliver Cromwell ([London Metropolitan Archives, 2013](#); [Newton, 1857](#); [June 1654: An Ordinance for the Regulation of Hackney-Coachmen in London and the places adjacent, 1911](#); [Lordan, 2018](#)). However, in 1851 the Great Exhibition in Hyde Park revealed incompetent navigation skills of the carriage drivers of those days. These initiated a series of complaints and forced authorities in the following years to set up stricter qualification requirements for drivers to test their knowledge of important streets, squares and public buildings, similar to the current *Knowledge of London* ([Lordan, 2018](#); [A to Z from Collins - The Knowledge, 2020](#); [The Knowledge, London's Legendary Taxi-Driver Test Puts Up a Fight in the Age of GPS, 2014](#)). This scheme was then officially introduced in 1865 ([Learn the Knowledge of London, Transport for London, n.d.](#)). The requirements in relation to the content of the knowledge have since hardly changed and remained in place ([The Knowledge, 2020](#)) despite the technological innovations that have produced navigation aids, such as GPS devices, that facilitate and guide navigation. The following sections will outline how this is achieved by taxi drivers.

The Blue Book

In order to help students to acquire the fundamentals of the Knowledge of London, the Blue Book (the origin of this name is unclear) was designed, which, in its current form, was put into place in 2000 (interview with K.T., **Appendix A**). It contains 320 origin-destination pairs, the corresponding runs, as well as additional points related to tourism, leisure, sports, housing, health, education and administration ([Electronic blue book, 2019](#)). In total, there are about 26,000 different streets and roads ([Eleanor Cross Knowledge School, 2017](#)) and more than 5,000 points ([Full set of Blue Book Runs, 2020](#))

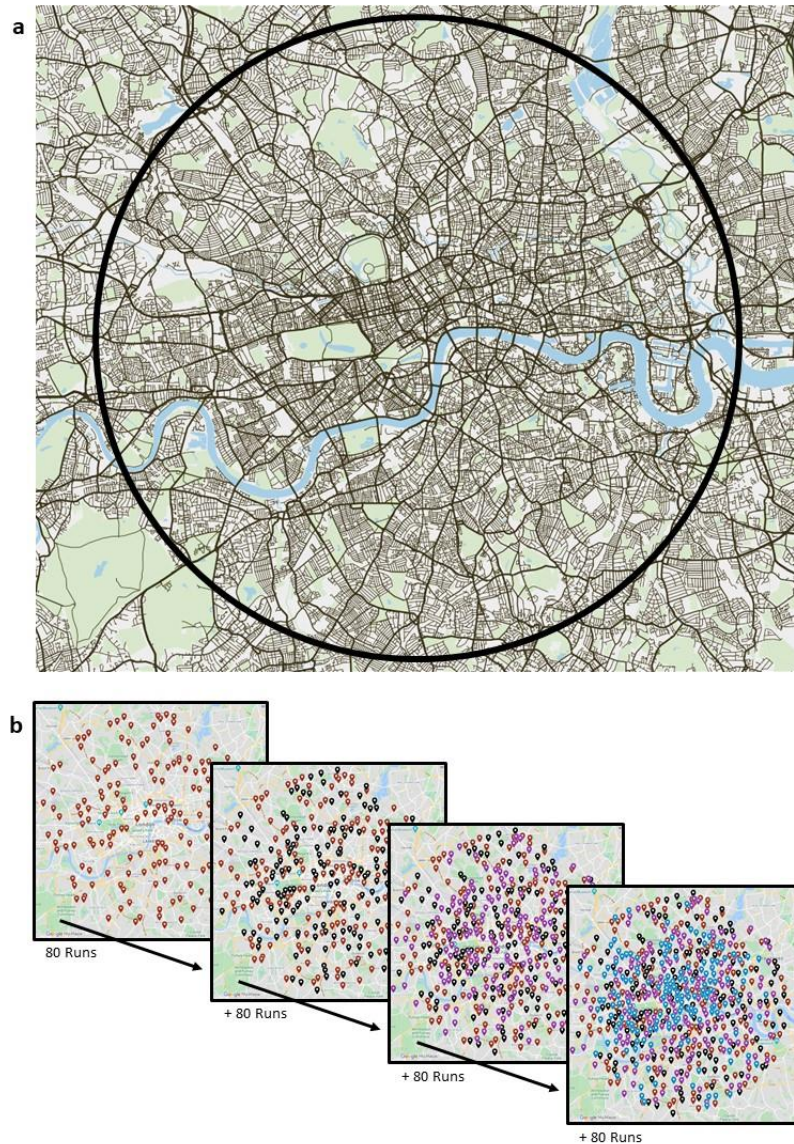


Figure 2.1. The Knowledge of London and the Blue Book. (a) London taxi driver students are expected to learn the street network and all potential points of interest within the six-mile radius around Charing Cross (black circle), which is called the ‘Knowledge of London’. (b) To support the learning process of this area, the Blue Book has been put into place. It contains 320 origin-destination pairs and the shortest route (i.e. ‘run’) connecting those pairs. When mapped chronologically in groups of 80 runs, the network of origin-destination pairs starts overlapping and becomes denser. **Red:** the first layer of the first 80 origin-destination pairs. **Black:** The second layer of the origin-destination pairs for Runs 81-160. **Purple:** The third layer of origin-destination pairs for Runs 161-240. **Blue:** The final layer of the last 80 origin-destination pairs for Runs 241-320. Map sources: (a) [Mapbox](#), (b) [My Maps](#) by Google Maps.

listed in the knowledge schools’ versions of the Blue Book. However, this knowledge is incomplete. By the time students qualify, they will have extended their knowledge to identify more than 100,000 points ([The London Taxi Experience - The Knowledge, 2020](#)) in a street network of about 53,000 streets ([OS MasterMap Integrated Transport Network, 2018](#)) that covers not only the six-mile area, but extends to all London boroughs including major routes in the suburbs.

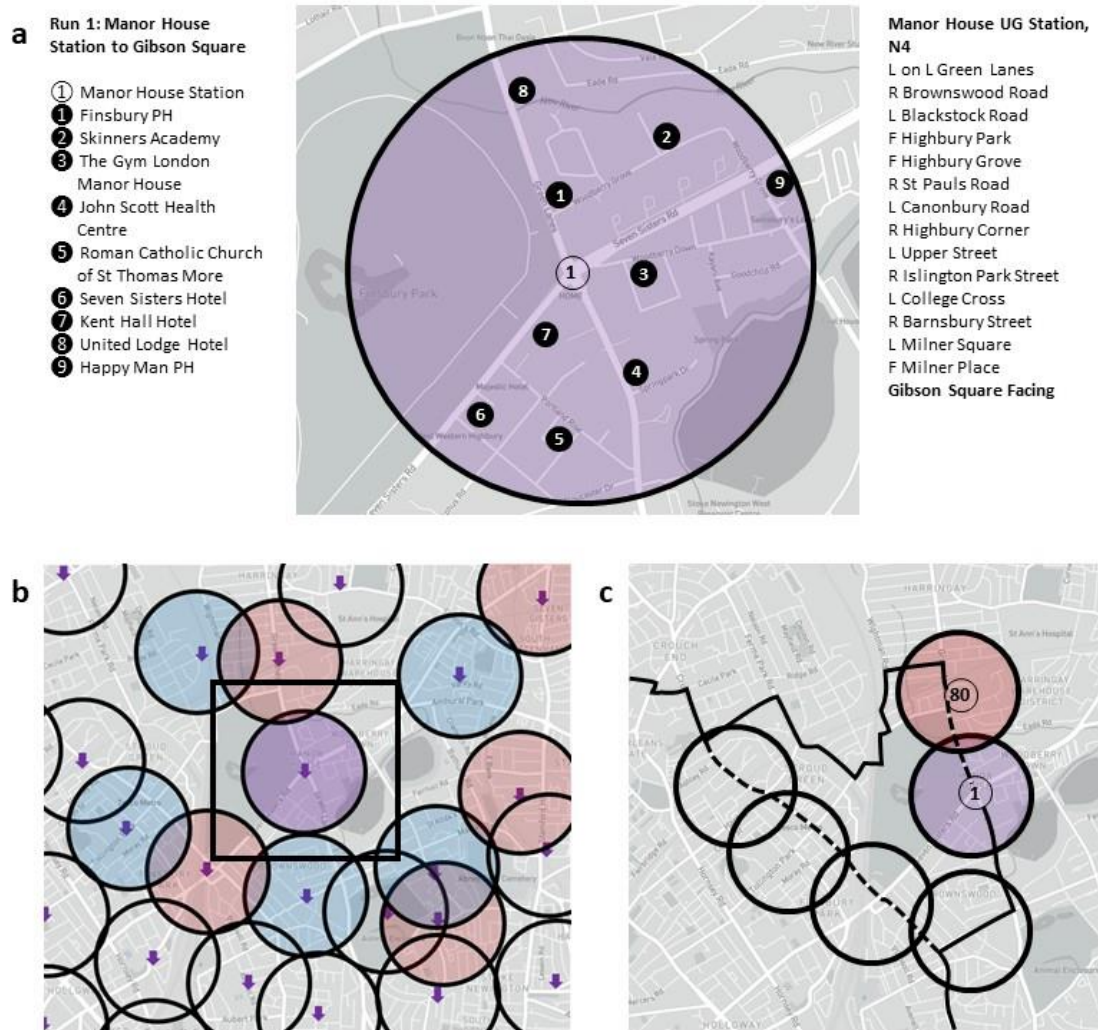


Figure 2.2. The points of the Blue Book. Each origin-destination pair of the Blue Book is presented in relation to its quarter-mile area. The origin of a run, here Run 1 (a), Manor House Station, and the corresponding quarter mile radius (black circle) with additional 8 other points of interest (numbered 1-8) are marked in a map. Labels are provided in a legend (left) and the most direct route (i.e. ‘run’) to the destination, including driving instructions (L on L: leave on left, L: left, R: right; F: forward) are listed on the right. The dense network of origin-destination pairs (b) results in an overlay of the neighbouring quarter-mile radii (black circles around purple arrows). For Manor House Station (purple circle) neighbouring quarter-mile origins and destinations are highlighted in blue and red, respectively. These quarter-miles are covering the six-mile radius in London by linking places of interest through linking runs (c) as indicated by the dashed lines connecting Run 1 from Manor House Station and Run 80, ending at Harringay Green Lanes Station. Source: Figures are based on learning material from [Taxi Trade Promotions](#).

The 320 origin-destination pairs of the Blue Book with their corresponding runs are structured into 20 lists of 16 pairs each, which are designed to systematically cover the six-mile radius: In a chronological order, as listed in the Blue Book, the majority of origin-destination pairs have an origin in the same postal districts as the destination of the previous origin-destination pair and spread across London throughout each list ([Electronic blue book, 2019](#)). When mapped in layers of four, the first 80 runs (i.e. five

lists) provide an initial, but rough coverage of London, which becomes more dense with each of the remaining three layers that are shifted slightly against each other to fill in the gaps (**Figure 2.1b**).

The quarter-miles

Each of the origins and destinations in the Blue Book also require students to learn the nearby environment within the quarter mile range. That area around a Blue Book point is called the ‘*quarter mile radius*’, or in short: the ‘*quarter-miles*’ and is considered as ideal for learning small areas of the environment without overloading students with information (interview with K.T., **Appendix A**; [Learn the Knowledge of London, Transport for London, n.d.](#); [Electronic blue book, 2019](#)). For the first and most famous run, which connects Manor House Station to Gibson Square, the quarter-mile radius is illustrated in **Figure 2.3a**. It contains about 8 additional points of interest, numbered 1-8. These are chosen by each knowledge school individually and can thus differ between schools. The additional points serve as initial motivation for students to explore the quarter-miles and learn which streets link these points to each other, again without risking information overload (interview with K.T., **Appendix A**). Knowledge of the remaining, unmentioned points in the area will be obtained by each student gradually as they progress through the Knowledge of London by studying maps and exploring the quarter-miles in person.

Mapping the origin-destination pairs with their corresponding quarter-miles, highlights how the areas locally link to each other (**Figure 2.3b**). To create such an overlap that sufficiently covers the whole six-mile area around Charing Cross (also see **Figure 2.3a**), 640 points are required, thus explaining the total number of 320 Blue Book runs. Since each point is closely surrounded by nearby origins and destinations of other runs, information is provided about how an area can be approached from or left in different directions. For Manor House (**Figure 2.3b**) these points have been indicated by blue and red quarter-miles for nearby origins and destinations, respectively, in **Figure 2.3b**. To visualise this information across the whole six-mile area of London and keep track of their progress whilst learning the Blue Book, trainee taxi drivers mark the origins and destinations, including the quarter-miles, in a large, all London map **Figure 2.3a and b**, source: Knowledge Point Central, Brewery Road, London, UK).

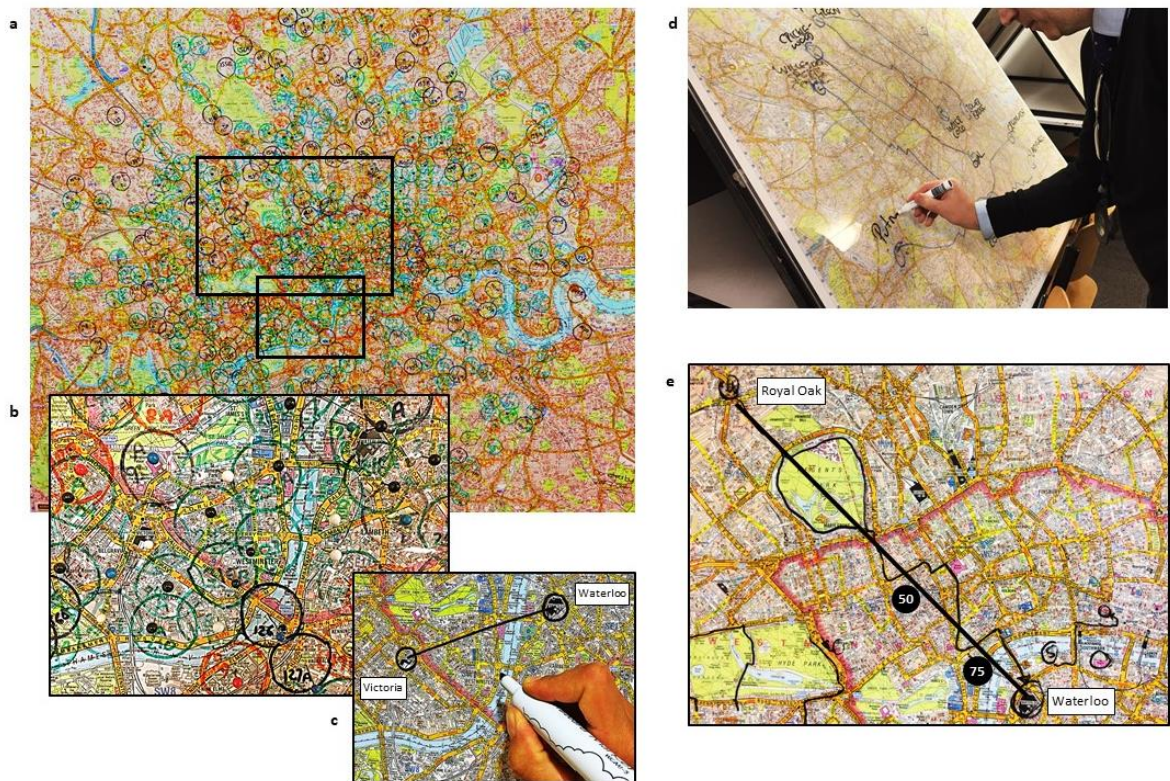


Figure 2.3. Example of Knowledge school material in use. In Knowledge schools, wallpaper maps (a) are used to illustrate the coverage of London within the six-mile area by the quarter-mile radii (b). These maps support the learning of relations between two places and clear up misconceptions such as Victoria being located further north than Waterloo, which is owed to a change in direction of the River Thames (c). ‘The cottoning up of two points’, a piece of string that is used to create a direct line between the points, is a common method to help with directional studies (c) and planning the most direct routes (d, e). Additionally, students use 50% and 75% markers along the direct line (e) to create subgoals that help to plan the runs. Source: Knowledge Point School, Brewery Road, London, UK.

Studying maps by visualising the topological relationship between areas also helps to avoid misconceptions about the city’s geography that could lead to mistakes in route planning. For instance, deviations from the more generally perceived west-east alignment of the river Thames can cause distortions: Often Victoria station, located north of the river, is incorrectly perceived to be also located further north than Waterloo Station, which is on the southern side of the river, but further east than Victoria (see **Figure 2.3c**). This misconception is due to a bend of the river Thames, that causes the river to flow north (instead of east) between Victoria and Waterloo.

The Runs

In the Blue Book, the 320 runs connect the origin-destination pairs through the shortest route for each pair. These pairs were chosen to create runs that are about two to three miles long and mainly follow trunk roads (i.e. most important roads in London after

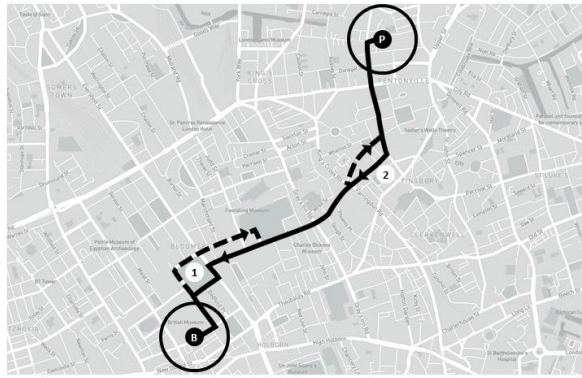


Figure 2.4. Runs and reverses runs. Due to one-way systems or turning restrictions, some runs differ when planned in reverse (dashed line), not allowing to simply invert the original sequence of streets taken (black line). This is the case for the run from Islington Police station (P) to the British Museum (B). When reversed, the one-way systems at Russell Square (1) and at Margery Street (2) require adaptation to traffic rules, resulting in differences between the runs and its reverse run. Figure is based on learning material from [Taxi Trade Promotions](#).

motorways, providing an important link to major cities and other places of importance, with segregated lanes in opposite directions, see [Key:highway, 2020](#)) and primary roads (i.e. most important roads in London after trunk roads, usually with two lanes and no separation between directions, linking larger towns or areas, see [Key:highway, 2020](#)). Since these are often printed in orange and yellow in paper maps, taxi drivers also refer to them as ‘*Oranges and Lemons*’ (interview with K.T., **Appendix A**). Trainee taxi drivers visualise these runs on all London maps to learn and practice recalling them (**Figure 2.3d**, credit: Knowledge Point Central, Brewery Road, London, UK). Knowledge schools provide the 320 runs for the points of the Blue Book, but encourage students to plan these runs before checking the up-to-date solution. In order to plan a run using the shortest route and avoid major deviations as required during the examination phase, drawing the direct line (i.e. ‘*as the crow would fly*’) or spanning a piece of cotton between the points instead (which is also called *cottoning up*) is essential (**Figure 2.3e**). This so-called ‘*cottoning up*’ also helps students to learn relations between places (**Figure 2.3c**) and visualise the map to avoid obstacles, such as Regent’s Parks, or to select bridges for crossing the river (**Figure 2.3e**) during the ‘*call out*’ of the run (i.e. the recall of the shortest route without using a map). Additionally, it provides opportunities to set subgoals, the ‘*50% and 75% markers*’, where the line coincides with major roads and bridges halfway or three quarters along the line to help students with their planning (**Figure 2.3e**). Due to one-way streets and turning restrictions, reverse runs from the initial destination to the initial origin can differ. Therefore, the streets and roads cannot simply be called in reverse order, but they have to be learned additionally (**Figure 2.4**).



Figure 2.5. Network of Blue Book runs. A visualisation of the 320 runs that connect the corresponding origin-destination pairs of the Blue Book forms a dense network of routes that overlaps, similar to the quarter-mile radii (a). Across the network, density varies and is less dense closer to the six-mile boundary (b) than in central London (c). This overlap also shows that more routes run through areas with higher irregularity in the street network (d) than areas of a more regular street network (e) in central London. Source: Adapted from Blue Book mapping by ProfEd Manley, University of Leeds

The Runs of the Blue Book form a network of routes that covers the six-mile area centred around Charing Cross (**Figure 2.5a**). However, the coverage of the London street network by the Blue Book runs systematically varies in density with respect to the distribution of points and the complexity of the street network: At its boundaries (**Figure 2.5b**) this network is less dense than in central London, where the runs are also overlapping more often (**Figure 2.5c**). This additionally reflects that more points of interest are being located closer to the centre of London, whereas residential areas are more likely to cover larger areas at the boundaries of the six-mile radius. Similarly, areas of London with a more regular street network, as in Marylebone and Fitzrovia, are covered by less runs (**Figure 2.5d**) than areas with a more complex and irregular street network, such as South Kensington and Chelsea (**Figure 2.5e**), which require more practice to learn.

Linking the Runs

Since the Blue Book runs focus on connecting origin-destination pairs about three miles apart from each other through main artery roads, they provide the main grid for efficiently travelling between those origin-destination pairs. In contrast, minor roads and the areas between the *Oranges and Lemons* (i.e. main roads that are printed in yellow and orange in most maps) are learnt by studying the quarter-miles and linking the additional points in those areas to each other (**Figure 2.3a** and **2b**). Further understanding and flexible linking is gained from the Blue Book runs as students start seeing where a Blue Book run would have continued to take a driver and how another, second run would have become a continuation of the first, if the initial run had not turned off the major road (interview with K.T., **Appendix A**). Ultimately, a combination of this knowledge enables trainee drivers to link the Blue Book runs efficiently where the runs intersect, or through minor roads of the quarter miles, where no intersection is available (**Figure 2.3c**), to cover large distances across London. Over time, links become more efficient as the Knowledge is ingrained and minor roads are integrated to create shortcuts where possible, so that the Blue Book is no longer perceived as a list of individual routes, but as a whole network (interview with K.T., **Appendix A**).

Table 2.1. Learning techniques used in Knowledge schools.

Learning technique	Supported skill and knowledge
A) Map Study	Bird's eye view:
- General Use of Maps	<ul style="list-style-type: none"> • Visualising street network • Relational knowledge of streets and areas • Areal knowledge (e.g. quarter miles) • Traffic rules (e.g. one-way systems, turning restrictions) • Sequential order of streets
- Dumbbell Method^{1, 2}	<ul style="list-style-type: none"> • Relational knowledge of places • Areal knowledge
- Linking Runs	<ul style="list-style-type: none"> • Flexible and efficient route planning
- Cottoning Up	<ul style="list-style-type: none"> • Efficient route planning • Relational knowledge of places
- 50% & 75% Markers	<ul style="list-style-type: none"> • Efficient route planning • Relational knowledge of places
- Memory Techniques¹:	<ul style="list-style-type: none"> • Memorising groups of streets in consecutive order (1,2,3) • Relational knowledge of streets in an area (e.g. quarter miles) (4) • Visualising street network (4) • Relation to personal memories (5)
(1) Acronyms & Mnemonics	
(2) Short stories	
(3) Method of Loci	
(4) Historical connections	
(5) Personal connections	
B) In-Situ Experience	In-Street View
- Travelling in Street	<ul style="list-style-type: none"> • Sequential order of streets • Experience
- Mental Simulation	<ul style="list-style-type: none"> • Visualising places and streets • Sequential order of streets
C) Combination of the Above	Bird's eye & In-Street View
- Call Over Partner*	
- Practice Material	Combination of all to simulate examination and fares
- Exam Questions	

¹Lordan, 2018;

²Learn the Knowledge of London,

Learning Methods

The progress that Knowledge students have to make from learning the first points and runs to flexibly plan routes all across London is supported through a range of learning techniques as listed in **Table 2.1**. These methods can be categorized into theoretical, map-related studies and practical, ‘*in-situ*’ experiences (interview with K.T., **Appendix A**; [Lordan, 2018](#)). Both support the development of planning strategies that are later used in situations that require route planning, such as practicing runs with a ‘*call over partner*’ (i.e. a Knowledge school study partner) in preparation for exams and when driving a taxi as a qualified driver.

In general, maps are used to learn the structure of the street network from a *bird’s eye view*, to obtain knowledge about relations between places and areas (e.g. quarter-miles and boroughs), traffic rules that can limit route planning due to one-way systems and turning restrictions, as well as the sequential order of streets for runs. At the beginning of studying the knowledge, this information is obtained mainly through the ‘*dumbbell method*’, which requires students to visualise Blue Book runs by tracing them on the map from the origin to the destination, including variations by using points in the respective quarter-miles, and thus creating ‘dumbbells’ on the map (**Figure 2.4**). This method is later extended to other places, as students learn to flexibly link runs and cover larger distances across London, supported by ‘*cottoning-up*’ and the use of subgoals, the 50% markers (interview with K.T., **Appendix A**). These 50% markers are bridges, if the river needs to be crossed, or other major roads and places. Additional subgoals are added before and after as needed to help give initial direction for the route planning without overwhelming the students. Both methods, the cottoning-up and the 50% markers, when used during initial stages of the training, help students to correctly visualise the map and relations between places. At a later stage of the Knowledge, when route planning is carried out mentally and without a physical map, these methods are integrated in the planning process automatically. To help students memorize sequences of street names that are often used for runs, different memory techniques are applied during the learning process and often even remembered years after obtaining the license. The most common techniques are creations of acronyms and mnemonics, inventions of short stories, or mental walks through rooms of an imagined house by integrating real place and street names in the invented stories or walks of a house, or historical connections and personal

memories that logically structure nearby places and explain the names given ([Lordan, 2018](#)).

Location specific information from an *in-street view* is learnt through ‘*in-situ*’ visits to the 320 origin-destination pairs of the Blue Book, their quarter miles and driving the corresponding runs. These visits - carried out multiple times, often on a scooter with a map of the Blue Book run attached to the windscreen - are essential to learning and recalling the Knowledge. During these visits exploring the quarter-miles and doing the runs, trainee drivers gather experience of the environment. This experience promotes memories related to places in the area that help the recall of sequences of streets, places of interest and specific traffic rules that have to be obeyed. These memories become an essential source of information when planning and calling out runs, as students use them for mental simulations that facilitate decisions about where to pick up or set down passengers, in which direction to leave or to approach an area and to find the most optimal route.

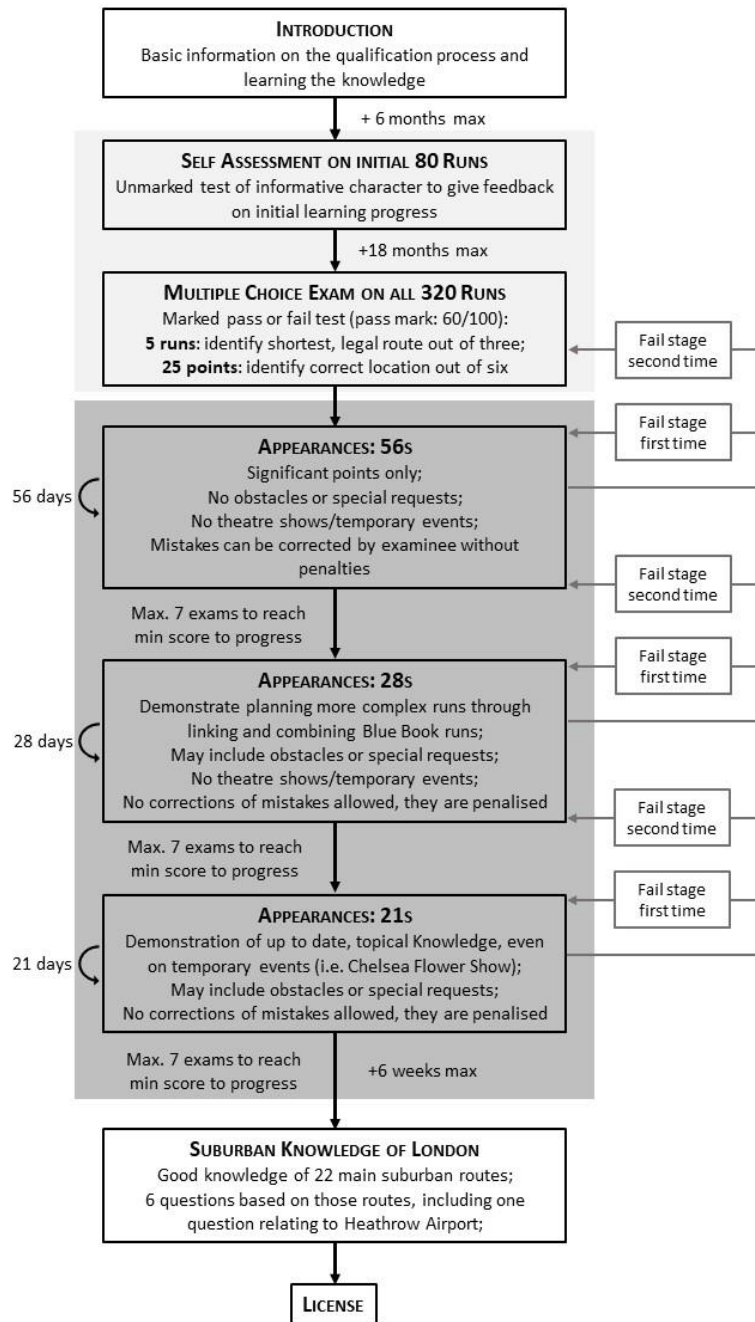


Figure 2.6. Knowledge examination process. The initial stage (light grey) of the Knowledge examination process provides feedback (*Self Assessment*) on the individual progress of learning the first 80 runs of the Blue Book and assesses the minimum knowledge on all 320 Blue Book runs needed (*Multiple Choice Exam*) to start the oral examination (*Appearances*). The main part of the examination process (dark grey) consists of a series of oral examinations, the so-called ‘appearances’, consisting of three different stages (the 56s, 28s and 21s, named after the intervals between each exam in the corresponding stage). Even though the requirements to students sitting between exams become more rigorous as they proceed, there are general rules that apply across all stages. These are related to the general layout of each appearance (e.g. duration, number of runs), expectations (e.g. shortest route), format of call out (e.g. identifying the location of origin and destination, sequentially naming streets and providing turning instructions), penalties (e.g. traffic rule violations, deviations from shortest route, hesitations), awarded points and progressing to the next stage. Following the appearances, students are required to pass an exam on suburban knowledge before they obtain their license. Source: Adapted from [Learn the Knowledge of London](#); [Knowledge of London learning and examination process](#), p. 21

Assessment Scheme

The assessment scheme for trainee taxi drivers in London was designed to support the learning process and guide students from early stages of learning the initial Blue Book runs to final stages, where their knowledge of London and suburban artery roads is rigorously challenged (**Figure 2.6**; interview with K.T., **Appendix A**, [Learn the Knowledge of London, Transport for London, n.d](#)). Initially, Knowledge schools offer an introductory class to provide basic information and an overview of the content of the Knowledge, including expectations, procedures and requirements of the qualification process, before preparatory examinations (**Figure 2.6**, light grey) can be taken. Within the first six months of starting the knowledge, students are expected to sit an assessment that is testing the knowledge on the initial 80 runs (five lists) of the Blue Book. Even though this assessment is unmarked, it is obligatory and of supportive and informative purpose at the same time, because feedback is given and discussed with teachers to help students identify problems in their learning process that need adjustment at an early stage to enable students successfully progress at later stages. Following this initial self-assessment, students have 18 months to sit a marked multiple-choice exam that tests their knowledge of the Blue Book, to ensure they have acquired the basics that are necessary to progress to the appearance stages (**Figure 2.6**, dark grey). To test this, the multiple-choice exams consist of two parts, where (a) the shortest, legal route out of three possibilities has to be identified for 5 randomly chosen Blue Book runs, and (b) the correct location out of six possible locations has to be selected for 25 points of interest that are likely to be part of the learning of the Blue Book runs.

After passing the two entry assessments, trainee taxi drivers enter what is known as the ‘*appearances*’, which is a set of oral examinations. At each *appearance*, students are expected to call runs from any two points that the examiners name. The *appearances* also comprise the longest and most difficult part of the Knowledge examination process and it is quite common that several of the stages have to be re-taken by students due to shorter intervals between appearances coupled with the growing expectations of the examiners. In total, there are three stages of appearances, the 56s, 28s and 21s, which correspond to intervals (in number of days) between any two appearances of the corresponding stage.

Even though the requirements for students sitting these exams become more rigorous as they proceed, there are general rules that apply across all stages: Each appearance is about 20 min long and can consist of up to 4 runs that students have to call, using the

shortest route, disregarding traffic and temporary roadworks. The *call outs* (i.e. naming streets in sequential order) include identifying the location of the origin and destination (i.e. the correct street), naming streets and giving turning directions along the run in correct sequential order, as well as including instructions for leaving and setting down passengers. Possible errors that will cause deductions of points are incorrect street names, any divergence from the shortest route, violation of traffic rules, impossible leaving or setting down instructions and hesitations during the call of the run. In each appearance, 3-6 points are awarded and 12 points are needed to progress to the next stage. Per stage, students are allowed to fail a maximum of three appearances, before the stage has to be repeated (first time) or students have to go back to a previously successfully passed stage (failing second time), limiting the number of exams per stage to a maximum of 7 appearances.

In contrast to later appearance stages, the '56s' are very closely related to the Knowledge obtained from the Blue Book. Here, examiners closely stick to runs from the Blue Book, which reflects a good knowledge of primary and secondary roads (i.e. the '*oranges and lemons*') even taking into account differences in the choice of additional points that are provided in the different version of the Blue Book study material (**Figure 2.3a**) and can vary between Knowledge schools. Additionally, runs are structured in a way that they will not contain obstacles (e.g. road closures), special requirements (e.g. requests to avoid traffic lights) or theatre shows and temporary events (e.g. Chelsea Flower Show) and students are allowed to correct mistakes by going back in their call out and changing their run. At the next stage, the '28s', examinees are expected to be able to link runs, using some minor roads and avoid obstacles or comply with special requests without being granted a chance of correcting runs any more. At the final stage, the 21s, trainee drivers have to demonstrate an overarching knowledge that is up to date and can additionally refer to particular topics (e.g. new tourist attractions, changes in hotel names) and temporary events, such as the Chelsea Flower Show.

After passing all appearances, the final exam is set to test the knowledge of suburban London. This knowledge covers 22 specific routes, including major points along those routes, radiating from the six-mile radius to the borough boundaries of London. In this final appearance, trainee drivers will be asked six questions relating to the 22 routes and points along those routes.

Daily planning process post qualification

For the learning process of a Knowledge student, the Blue Book is central, as it provides them with “*the ability to know where streets and roads are going to and where all those places are*” (interview with K.T., **Appendix A**). However, over the course of obtaining the Knowledge and learning how to link Blue Book runs efficiently, there seems to be a change in the perception of London. Initially it consists of distinct routes and locally focused areas on a map, which over the course of time fade into a connected, large-scale, inseparable network of streets and places in the real world. During consulting conversations with taxi drivers, they reported that they just knew where they had to go without much planning. For well-known places, Robert Lordan described the planning and execution of a run as “*I wouldn’t even have to think; my brain would be on autopilot. [...] like a moth drawn to a light!*” (email conversation with Robert Lordan, **Appendix B**). For longer distances, subgoals, as trained with the 50% markers, are used automatically: “*I’d find that my brain would often plan in stages; essentially I’d envision a set of waypoints and the route would then come to me as I progressed*” (email conversation with Robert Lordan, **Appendix B**).

The overall impact of the knowledge also seems to foster a deeper connection (“*I already loved the city, but in studying it I now love it all the more. It feels like an old, familiar friend*”, email conversation with Robert Lordan, **Appendix B**), a constant drive to stay up to date with changes in the city (“*The Knowledge made me crave detail! To this day I want to know as much as I can about London*”, email conversation with Robert Lordan, **Appendix B**) and new curiosity (“*The Knowledge also makes you want to know as much as you can about new locations that you’ve never been to before*”, email conversation with Robert Lordan, **Appendix B**).

2.5. Discussion

In this study information was collected on the process by which licensed London taxi drivers learn and are examined on the Knowledge of London, a combination of the knowledge of the street network, points of interest and flexible planning ability. To learn the Knowledge of London, taxi drivers use a wide range of theoretical and in-situ methods. This primarily includes map-related studies, based on an overlapping network of basic points of interest and routes that systematically cover London, as well as visits to these locations used in the Blue Book and their retracing of the theoretically learnt

routes on motorbikes. Both experiences are vital for linking theoretically learned information to specific real-world locations and flexible navigation in this environment. For research these observations can provide important insight in various ways. Spatial learning of a novel environment could be optimized through a combination of map-based and in-situ navigation to allow for a better mental representation of the environment. Especially in settings that require flexible navigation due to the terrain and that explore the link between hippocampal structure and memory, or when AI systems are developed that learn large amounts of information for flexibly navigating space, the learning and understanding spatial relations of the testing environment is vital.

The Knowledge and spatial learning in research settings

In contrast to taxi drivers, most non-experts learn how to navigate spaces and confidently find routes differently, mainly relying on experience in a locally limited area (e.g. neighbourhoods close to home or work). They mainly rely on experience and often use location specific cues to adapt their route rather than systematically planning ahead subgoals of the route, or visualising places and potential options. In this sense, taxi drivers are special, since their learning of the Knowledge of London enables them to ‘instantly know’ where they are going, similar to non-expert route planners in a familiar neighbourhood, but with the main difference being that for taxi drivers this familiarity of a ‘neighbourhood’ expands to all of London. In research, a wide range of studies have explored spatial navigation and relied on different methods of spatial learning to study aspects of spatial memory and navigation, such as strategies, performance, orientation, a hierarchical representation of space, as well as route planning and mental walks. The environment in which the studies were carried out were often controlled, virtual environment or virtual replication of a real-world environment, resembling ‘ghost-towns’ with no other agents moving in them. Here, spatial learning took place through instruction-guided navigation (e.g. [Brunec, Ozubko, Ander, Guo, Moscovitch, & Barense, 2020](#); [Wiener, Condappa, Harris & Wolbers, 2013](#); [Meilinger, Knauff & Buelthoff, 2010](#); [Meilinger, Riecke & Buelthoff, 2013](#)), map-based navigation (e.g. [Coutrot, A., Silva, R., Manley, E., De Cothi, W., Sami, S., Bohbot, V. D., Wiener, J.M., Hoelscher, C., Dalton, R.C., Hornberger, M., & Spiers, H. J., 2018](#); [Coutrot, Schmidt, Coutrot, Pittman, Hong, Wiener, Hölscher, Dalton, Hornberger, & Spiers, 2019](#); [Grison, Gyselinck, Burkhardt & Wiener, 2017](#)), landmark navigation (e.g. [Wiener & Mallot,](#)

[2003](#); [Wiener, Schnee & Mallot, 2004](#); [Wiener, Kmecova & Condappa, 2012](#); [Wiener, Condappa, Harris & Wolbers, 2013](#); [Astur, Germain, Baker, Calhoun, Pearlson & Constable, 2005](#); [Newman, Caplan, Kirschner, Korolev, Sekuler & Kahana, 2007](#)), *in-situ* training phases (e.g. [Javadi, Emo, Howard, Zisch, Yu, Knight, Silva & Spiers, 2017](#); [Wiener & Mallot, 2003](#); [Wiener, Schnee & Mallot, 2004](#); [Spriggs, Kirk & Skelton, 2018](#); [Warren, Rothman, Schnapp & Ericson, 2017](#); [Newman, Caplan, Kirschner, Korolev, Sekuler & Kahana, 2007](#)) or relied on experience and pre-existing knowledge of an environment (e.g. [Hölscher, Tenbrink & Wiener, 2011](#); [Meilinger, Frankenstein & Bulthoff, 2014](#); [Frankenstein, Mohler, Bulthoff & Mailinger, 2012](#); [Bonasia, Blommestejn, Moscovitch, 2015](#)). In a novel environment, landmark and map use have been studied to better understand wayfinding (e.g. [Hölscher, Meilinger, Vrachliotis, Brösamle & Knauff, 2006](#); [Hölscher, Büchner, Meilinger & Strube, 2009](#)).

These studies show a range of similar methods that taxi drivers use for their training, such as memorising a map or routes on a map to find a destination or goal location, respectively, as well as active *in-situ* training in an environment. Relying on experience and pre-existing knowledge of a familiar environment like a city centre (e.g. [Hölscher, Tenbrink & Wiener, 2011](#)) and the use of landmarks during a wayfinding closely reflect the knowledge and strategies that taxi drivers are trained on and later use on a daily basis to navigate in London ([Spiers & Maguire, 2008](#)). However, during their training, taxi drivers combine these methods efficiently and repeatedly, whereas study designs only rely on single strategies at a restricted time scale. On the other hand, mental visualizations have not been used for training purposes in research and mainly served as a means to study memory components of spatial representations (e.g. [Bonasia, Blommestejn, Moscovitch, 2015](#)). For taxi drivers, these mental visualizations are key to efficient route planning (interview with K.T., **Appendix A**, notes from lessons in Knowledge Point Central, Brewery Road, London, UK). Taken together, these strategies can ultimately explain responses found by Spiers and Maguire ([2008](#)), who studied strategies and components of the planning process carried out by licensed London taxi drivers during navigation in a virtual representation of London. In this study, verbal reports and comments on taxi drivers' route planning highlighted tendencies of sequential planning to subgoals along the route, comparison of route alternatives or mental visualisations of places and route sequences. These observations from Spiers and Maguire ([2008](#)) can now be better understood and explained in light of this review of the training process of licensed London taxi drivers.

Other strategies, such as guided navigation through a novel, virtual environment (e.g. [Wiener, Condappa, Harris & Wolbers, 2013](#)) have not found an application in the training phase of taxi drivers, not even as an adapted in-street view version of London. This might be explained through constant changes of the environment (e.g. temporary road closures, name changes of hotels or restaurants, and temporary events, such as Winter Wonderland) that are difficult to constantly keep updated close to the time in a virtual replication of London, but are considered essential knowledge, especially at later stages of the training process (i.e. the ‘21s’ of the appearances, cf. **Figure 2.6**).

The Knowledge and spatial concepts

The appearances (**Figure 2.6**) suggest a layered learning of the London street network as they initially focus on the Blue Book runs or runs along main roads (i.e. ‘*oranges and lemons*’), and only at later stages integrate minor roads in the assessments. However, the actual learning process requires students to learn minor roads in the quarter-miles from the beginning (i.e. with the first run). This differs from the requirements in other cities, such as Paris, where drivers have to demonstrate knowledge of a limited number of major points of interest, as well as predefined major routes. There, taxi drivers are expected to expand their knowledge to the minor street network through experience whilst working as a taxi driver ([Prefecture de Police, Demarches & Services, 2020](#); [Skok, 2004](#)). Similar to the ‘oranges and lemons’ of the London street network, the Parisian street network covers the city in two layers: The base network, an uneven grid-like pattern that allows travel on major roads and helps to reduce traffic on the secondary network, a network of minor streets ([Pailhous, 1969](#), 1984; [Chase, 1982](#)). For Parisian taxi drivers, such a selective learning of the base network was found to be also reflected in their mental representation of the street network in form of these two layers ([Pailhous, 1969](#), 1984). In contrast to London taxi drivers, Parisian taxi drivers’ awareness of the secondary network only grows and becomes more efficient and optimal through experience rather than training and is almost non-existent at the beginning of their career ([Chase, 1982](#); [Giraud & Peruch, 1988](#), [Peruch, Giraud & Garling, 1989](#)).

The ability to additionally use mental simulations and in-street view of places for the route planning process has not been reported for taxi drivers in other cities. This ability is actively encouraged and trained in knowledge schools. Interestingly, teachers and examiners claim to know when students ‘see the points’ as they actively visualise origins

and destinations as part of their planning process (see interview with K.T., **Appendix A**; notes from lessons in Knowledge Point Central, Brewery Road, London, UK). In research, the ability to use spatial visualization strategies was found to differ between individuals, for instance as a result of age and experience ([Salthouse, Babcock, Skovronek, Mitchell & Palmon, 1990](#)), education levels or gender differences (e.g. [Wolbers & Hegarty, 2010](#); [Coluccia & Louse, 2004](#); [Montello, Lovelace, Golledge & Self, 1999](#); [Moffat, Hampson & Hatzipantelis, 1998](#); [Fennema & Sherman, 1977](#)). However, there is also some evidence suggesting that certain spatial visualisation skills could be improved through training, for instance with engineers ([Sorby, 2009](#)). With taxi drivers, the skill of visualising places has been reported in this study to improve with experience. This could be related to the saliency and quality of the memory a student has of locations and improve as trainee drivers revisit locations of the quarter-miles.

Further evidence for an extensive use of mental navigation through London can also be found in the way taxi drivers call the runs by using instructions and phrases such as ‘forward’, ‘left/right into’ and ‘comply’. These closely relate to an in-street view of the mentally planned route and indicate an egocentric reference frame for the call out. However, such linguistic phrases are only evidence of mental visualisations during the call out to communicate route-related information and reflect what would be experienced naturally when driving a customer to a destination. For the planning process, a development was observed away from an allocentric and towards an egocentric reference frame: During the early stages of the Knowledge training, the planning process is reported to rely on an allocentric reference frame by studying maps to train students on planning shortest paths (interview with K.T., **Appendix A**). At later stages, as experience is gained from planning runs and through in-situ visits to locations, an automatic awareness of the direction of travel or a particular route is developed (email conversation with Robert Lordan, **Appendix B**). Such experiences are also consistent with previous findings of verbal recalls from taxi drivers during a simulated in-street navigation ([Spiers & Maguire, 2008](#)) and individuals, who performed better on navigation tasks that involved instruction-guided navigation that matched the egocentric reference frames of navigators rather than an allocentric, external frame ([Ishikawa & Kiyomoto, 2008](#)).

Adaptivity of the Knowledge to contemporary methods of navigation

The approach that London has taken to train and test their taxi drivers on the Knowledge as described above, is historically motivated and has been retained over centuries since its implementation, only allowing for adaptations and improvements. This concept of learning all possible points, their locations, the street names and how to flexibly plan routes and adjust to specific requirements is globally unique. In contrast, other cities, such as Paris ([Prefecture de Police, Demarches & Services, 2002](#)) or Madrid ([Federación Profesional del Taxi de Madrid: Departamento de Formación, 2010](#); [Skok & Martinez, 2010](#)), often only require applicants of the trait to learn the major grid of the street network (i.e. the base network) and expect the knowledge of the minor street network (i.e. the secondary network) to be obtained through experience. Instead, taxi drivers are also required to demonstrate knowledge on other trade related areas, such as driving specific knowledge, professional regulations, safety and business management, a language test ([Skok, 2004](#)), or fares, legislations and personality ([Skok & Martinez, 2010](#)). Considering these alternative qualification requirements as in Paris or Madrid, the London qualification scheme as described above as a thorough knowledge of London seems to be frequently questioned with regards to its adequacy and value nowadays, in times of GPS systems that can guide navigation.

Given that GPS in general successfully supports navigation and thus is omnipresent in daily life, it remains open, why London taxi drivers continue to rely on their own abilities to plan routes. One potential answer could be an individual's sense of accomplishment of a difficult, and in this case, almost impossible task. London taxi drivers often find such a sense of achievement and pride in their ability to master challenging navigation tasks in a complex city only by using their own spatial memory instead of depending on external devices that could be sources of mistakes ([McKinlay, 2016](#)). This ability to flexibly navigate not only the base network, enables London taxi drivers to instantly follow their route plan even to points in the secondary network, quickly adapt to any changes on-route due to customer preferences or traffic flow (i.e. congestion or road closures) and avoid errors that might result from incorrect instructions given by passengers (e.g. [Lordan, 2018](#)), who might confuse Chelsea's buzzing shopping mile, King's Road, with the quiet King Street near St James's Park, Westminster. In contrast, taxi drivers in Paris, Madrid and other cities take years to acquire this type of knowledge in their cities and might never achieve a similar, almost flawless knowledge of their cities as some areas might be less

frequently travelled. Therefore, it is not surprising that there have been requests from cities like Tokyo for London Knowledge teachers to develop a similar method for taxi schools in their cities (interview with K.T., **Appendix A**). Moreover, their experience to filling the gaps in their knowledge might strongly rely on GPS devices, which have been found to impair spatial learning (e.g. [Ishikawa, Fujiwara, Imai & Okabe, 2008](#)) and interfere with spatial navigation ([McKinlay, 2016](#); [Meilinger, Knauff & Bühlhoff, 2008](#); [Johnson, Shea & Holloway, 2008](#)).

Even though the requirements for becoming a licensed London taxi driver and the amount of knowledge that has to be learned are constantly being challenged, from a research perspective this concept has contributed vital insight into spatial learning. The memory techniques used in knowledge schools to memories sequences of streets or links between areas ([Lordan, 2018](#)), the ‘*dumbbell method*’ that links small areas of the secondary network through routes on the base network, or mental visualisations of familiar places (**Table 2.1**) could initiate new methods of visualising and displaying spatial information in maps or GPS devices to facilitate sustainable spatial learning. Additionally, computational methods could be exploited to learn from the Knowledge of London and adopted for use in other cities worldwide. Learning how humans navigate, based on a network of shortest routes and small, interlinking areas, can provide valuable input to predict and support human navigation in other cities.

Improving the Knowledge of London

The knowledge in its current form, based on the 320 Blue Book runs, has been in place for about two decades, but the study methods (**Table 2.1**) have remained the same over decades going back in time a lot further. However, there has been a tendency of involving new technologies and creating online resources, such as apps that can hold and test students on the Blue Book runs. Other methods, that have not been adopted by schools, yet, could include a database of Blue Book video runs, interactive online maps and applications with the daily appearance points and updates, but these come with flaws as the following examples will show.

The Blue Book video runs database could be created from Blue Book practice runs of students and bridge between map-based studies and active in-situ travel. A complication could result from the constant changes in the environment (e.g. temporary changes to traffic rules, or restaurants and shops moving) if video material is not constantly updated.

Additionally, these videos would only partially cover what is learnt when actively travelling the run on a moped, which allows students to focus on spatial information that is of particular interest for their individual learning process (e.g. points they might find difficult), the driving experience itself that also trains students on local traffic rules, or the exploration of the quarter-miles that plays a major role when doing a run in-situ and would outperform passive and time consuming video-guided navigation ([Ishikawa, Fujiwara, Imai & Okabe, 2008](#)). Still, such videos could potentially find application in taught classrooms to analyse and better illustrate places and sections of runs.

In contrast to the video database, online maps and applications could provide a platform that can be more easily kept up to date, but with focus on Knowledge requirements that allow general contribution, similar to [OpenStreetMaps](#), and individual modification, as with Google My Maps ([My Maps, n.d.](#)), to support the individual learning process. Such a platform could additionally include updates on points asked in recent appearances that students use for preparation or an option to train with and challenge other students or their call-over partner. However, these platforms would not be able to replace the social situation students find themselves in at knowledge schools and when practicing face to face with their call-over partners, that also have a psychologically motivating, supportive effect. Neither can these digital maps overcome some obvious limitations due to screen sizes and compensate for a view of the ‘bigger picture’ that a wall-paper map is able to convey. As for the Blue Book video runs, digital applications could provide additional ways of input to support spatial learning.

Studying the training process of licensed London taxi drivers has provided a vital opportunity to better understand learning strategies and methods that efficiently support the learning process to an extent by which individuals acquire unique spatial knowledge to navigate an enormous street network independently from external support, such as GPS. Forming such mental representations of real-world spaces is essential, but it still remains unclear, how these representations are structured, for instance in regions and areas that would facilitate hierarchical planning. Here, an understanding of spatial structures, such as street network boundaries that segregate the environment and potentially contribute to a hierarchical representation, could more efficiently support the training process. However, such a segregation of the environment has not been explored before and the impact on route planning remains unknown. In the following, a novel approach has been taken to explore the perception of boundaries in the London street

network with licensed taxi drivers (**Chapter 3**) and how these impact route planning (**Chapter 4**).

3. MENTAL MAPS OF GEOGRAPHICAL BOUNDARIES IN LONDON

3.1. Abstract

Spatial boundaries have been widely studied in neuroscience, behavioural science and geoscience. They have been found to impact spatial memory and the mental representation of an environment, but it remains unclear how individuals mentally represent real-world cities and segregate such an environment based on street network structures. In this study, taxi drivers were asked to indicate streets they perceived as boundaries for London districts or between areas. Results highlight that agreement on perceived boundaries in an urban environment ranges across drivers from very low consensus with diversely perceived boundaries to strong consensus on a particular street. Data suggests that properties that contribute to this perception of boundary locations include prominence, topical distinctiveness, a regular, linear or almost rectangular outline and familiarity with the area. These findings provide insight into types of environmental features that give rise to consistent mental representations of boundaries that may impact spatial learning, navigation and route planning.

3.2. Introduction

Boundaries in an urban context are often found to separate or mark the limit of areas geographically within a larger environment. Spatial structures that are perceived as boundaries (e.g. rivers or train tracks) can impact navigation in an environment as they keep traffic from crossing over and force navigators to go through bottlenecks (e.g. bridges across a river). Other boundaries, such as area boundaries that separate regions, states or even countries, can be visually less prominent and are often only perceived when highlighted on maps, through road signs or border crossings. In contrast to their physical appearance, they impact on how the environment is mentally represented, as these boundaries can cause distortions of spatial properties, such as distance estimates (e.g. [Chase, 1982](#); [McNamara, 1986](#); [Okabayashi & Glynn, 1984](#); [Stevens & Coupe, 1978](#); [Kippel, Knuff, Hommel & Freska, 2004](#)), and facilitate a hierarchical organisation (e.g. [Hurts, 2005](#)). As places are recalled faster (e.g. [Chase, 1982](#)) and more precisely (e.g. [Stevens & Coupe, 1978](#)) within than across neighbourhoods, mental representations of complex cities like London, UK, are possibly impacted by perceived structures of the street network that function as boundaries. Such structures could potentially include main

roads that separate neighbourhoods or larger areas as a result of the historical development. However, neighbourhoods in cities like London, that developed as original cities expanded and settlements merged, often have no or more ambiguous boundaries (e.g. Bayswater), and for those areas with defined boundaries (e.g. Soho), it remains unclear which of those boundaries are ultimately perceived as such by humans.

Initially, European cities that developed over centuries and had clear historical boundaries, such as city walls (e.g. London Wall). These defence structures left their imprints on the street network and shaped the topography of cities like London within and beyond the protective walls as they allowed limited access to the city at particular points and connected the city to other places through those points. Often these connecting streets later became important artery roads as the city grew beyond its boundaries and settlements formed nearby or along those roads ([Mola: The London Evolution Animation, 2014](#); [Tatton-Brown, 1986](#); [Nicholas, 2014](#); [English Heritage, n.d.](#), [Simms, 2010](#)). Many modern cities have been built with the intention to save space, or structure and segregate the city in areas with different purposes to facilitate administration and navigation. Examples are the regular, square-shaped patterns of northern American cities, e.g. Manhattan, in New York, USA, or the cross-shape layout of Brasilia resembling a bird ([Epstein, 1973](#)). In contrast to these relatively modern cities, ancient, historical cities like London, often lack such a large-scale structure, but have multiple centres with a complex street network. In the 18th century, an extreme growth of the population forced the settlements surrounding London to connect through roads and to take in the unoccupied space in between populated areas until what is now known as Greater London was covered ([Mola: The London Evolution Animation, 2014](#); [Layers of London, 2020](#)).

Several of these roman and medieval roads have survived over centuries and become important main arteries in contemporary London: *Watling Street*, that ran north along Edgware Road towards St Alban's ([Lordan, 2018](#), [London's Roman Roads, 2013](#)), or *Portway*, running west from Farringdon Road along Oxford Street, at the northern edge of Soho and Mayfair ([London's Roman Roads, 2013](#)). In the City of London, most of the medieval street network is still in place ([Layers of London, 2020](#)) and streets, such as Cheapside, Poultry, Cornhill, Leadenhall St and Old Street, have hardly changed, except for their names (e.g. 'Westchap' to 'Cheapside', or 'Langburnestrate' to 'Lombard St').

Since many European cities share a similar history of population growth and merging settlements that lack modern, structured planning, the boundaries of areas in London are often unclear (e.g. Bayswater, Clerkenwell, Farringdon or Dalston). However, most

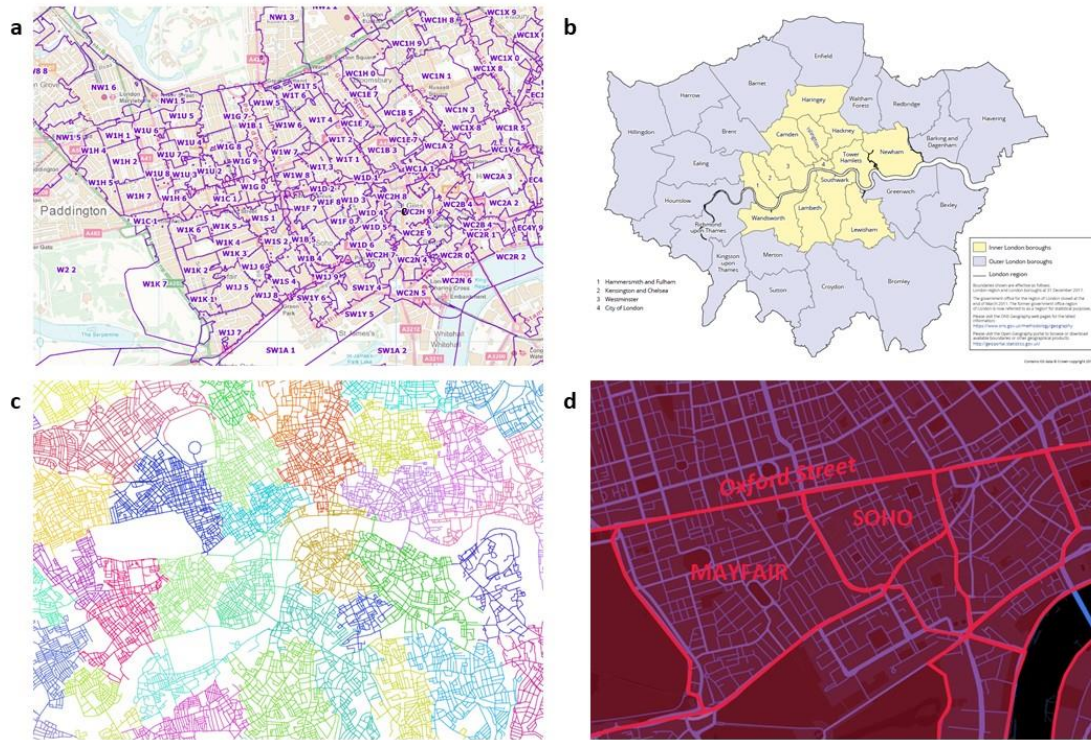


Figure 3.1. Types of boundaries in London. London has been segregated into areas with specific, well defined boundaries with different purposes. Administrative boundaries include small postal areas (a) or larger, locally governed boroughs (b). Computational clustering (c) based on street network properties highlight clusters with no clear street network boundaries as for postal areas and boroughs. Districts, such as Soho, Mayfair, Leicester Square and Covent Garden (d) partially reflect clustering structures and bridges between fine-grained postal areas and large-scale boroughs. Sources: (a) [Digimaps - Edina](#); (b) [Office for national statistics](#); (c) Gabriele Filomena, based on Lynch 1960; (d) Map source: [Mapbox](#)

predefined boundaries that exist only serve an administrative purpose ([Campari, 1996](#)) rather than facilitating a structured perception of the city. For instance, postal (**Figure 3.1a**), electoral, census and healthcare areas ([Open Geography Portal, 2020](#)) or boroughs (**Figure 3.1b**) define local competences and responsibilities for a collection of households and seldom reflect the topographical structures based on elements that humans would use to build a cognitive map (i.e. paths, edges, nodes, districts and landmarks; [Lynch, 1960](#)). Geographical approaches have used traffic flow (e.g. [Manley, Orr & Cheng, 2015](#); [Manley, 2014](#)) and topological clustering of the street network (e.g. [Filomena, Verstegen & Manley, 2019](#), [Jiang & Claramunt, 2004](#), [Masucci, Smith, Crooks & Batty, 2009](#), [Masucci, Arcaute, Hatna, Stanilov & Batty, 2015](#)) to identify potential regions in London or in other cities. These approaches, on the other hand, were mainly based on street network analytics, not accounting for human perception and the resulting clusters often lack structural boundaries that would spatially and perceptually separate regions (**Figure 3.1c**).

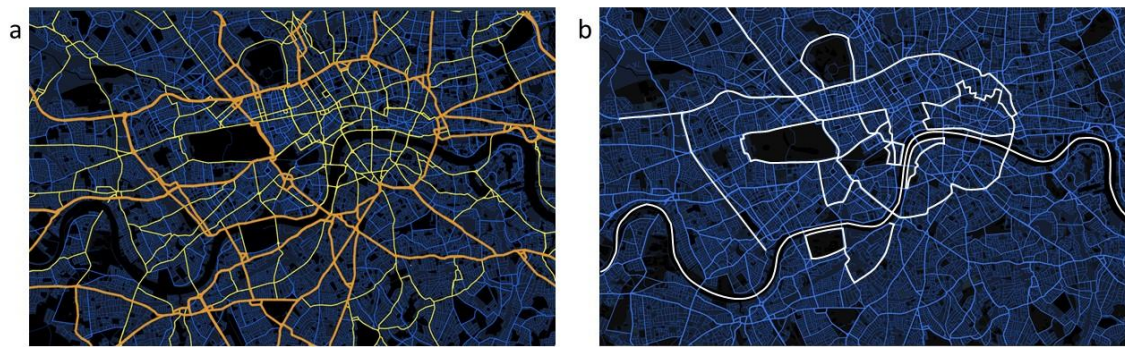


Figure 3.2. London street network representations. Segregation of the London street network into different road types (a) with major roads (orange and yellow) and minor roads (blue). Expected boundaries of the London street network (b). Base Layer Source: [Mapbox](#)

In contrast to these approaches, a consciously perceivable segregation of London could be based on street network measures, such as road types (**Figure 3.2a**) or methods of formal spatial analytics that represent spatial properties of the environment more likely linked to human behaviour. For instance, Parisian taxi drivers have been found to represent the street network in a hierarchical manner, using two layers: a basic network consisting of major roads (orange and yellow roads, **Figure 3.2a**) that enclose areas with a secondary network of minor roads (blue roads, **Figure 3.2a**; [Pailhous, 1969](#), 1984). However, it remains unclear if such a dual representation might be limited to navigation and route planning related purposes, rather than to define boundaries that distinguish between perceptible, distinct areas in a city.

Similarly, streets with a high importance for the street network might provide another perceivable grid that could segregate the street network. Such a representation could be better studied with spatial analytics, such as space syntax. Based on graph-theoretic properties (i.e. edges and nodes) the street network environment is abstractly represented through a graph. Such a representation allows to identify and formally analyse aspects of the street network and relate those to human behaviour ([Hiller & Hanson, 1989](#); [Hiller, 1996](#); [Hiller, Penn, Hanson, Grajewski & Xu, 1993](#)). For instance, space syntax represents the segments of each street by converting these street segments into nodes and street intersections to edges. Through such a segment-based approach, segment related aspects of the abstract street network graph can be studied, which are in contrast to traditional network analysis that focuses on intersection related aspects. These aspects indicate for each segment (a) *degree centrality*, a quantification of the number of connected street segments, (b) *closeness centrality*, the number of reachable segments within a certain radius, and (c) *betweenness centrality*, a measure of the frequency a segment would be

travelled when any two segments of the environment were connected through the shortest path. Thus, betweenness centrality can reflect the importance of a segment for the graph network and, when related back to the street network, highlight the importance of a street. Streets with high betweenness scores, such as Oxford street, could carry a boundary function as these streets are likely to have developed from roads that historically connected places of interest and separated areas that developed along those roads.

Additionally, since most administrative boundaries and computational clusters provide a complex segregation of London, it is not likely that such a regionalisation would be adopted by humans to generate a cognitive representation of London areas. Instead, some London districts might better meet the requirements to serve as areas with boundaries. Districts are often smaller than boroughs, with well-defined outlines anchored in the street network and often historically developed a conceptually distinct and popular purpose (cf. [Lynch, 1960](#)). For instance, Soho (**Figure 3.1d**) initially served as a park, before it was developed into an upper-class living area and now stands out because of theatre productions, night live and hosting the gay community. Similar developments of other London districts (e.g. Mayfair, cf. **Figure 3.1d**) and prominent parks (e.g. Hyde Park), with manifested boundaries, as well as the River Thames, which in itself divides London into ‘north of the river’ and ‘south of the river’, are more likely to trigger a segregated mental representation of London (**Figure 3.2b**).

In summary, this study aims to investigate whether London districts and other areas (e.g. parks) with topologically defined boundaries are perceived as such by London taxi drivers who have to navigate London daily. Whether features of the street network (e.g. main roads) could predict the likelihood of a street being a boundary was investigated. In particular, based on the above evidence, the following categories of boundaries for regions are expected: Prominent, topical districts with a distinct function that are embedded in a straight, regular street network are expected to be surrounded by streets that are perceived as street-network boundaries. Boundary streets should emerge around fully bounded geographical structures, such as parks. Additionally, there exist prominent geographical structures or prominent and straight main roads that separate areas and thus function as perceptual boundaries in themselves. In particular, the river is predicted to be highly conserved and act as a major barrier. Finally, the majority of boundaries are expected to be main roads.

Consequently, the following predictions can be derived for London: Boundaries for districts that fall in the above category of prominent districts with a regular street network,

such as Soho and Mayfair (see list of identified areas below in **Section 3.3, Methods**) will be more consistently identified than districts with irregular shapes (i.e. polygons), such as the City of London or streets that are minor roads. Similar to districts with distinct purpose, streets enclosing prominent parks, such as Hyde Park, Regent's Park and Battersea Park, will be more consistently identified as boundaries. The River Thames constitutes a prominent geographical structure that will be identified by all taxi drivers as a natural boundary separating areas south of the river from the rest of London.

3.3. Methods

For this study, licensed London taxi drivers were recruited to study consciously perceived boundaries of districts and areas. The taxi drivers' immaculate knowledge is based on years of training and daily experience of navigating around London that the general population would not be able to achieve without years of specific training as done in knowledge schools (see **Chapter 2**). Such an exhaustive knowledge allows to flexibly test each individual's perception of semantic boundaries across different areas in London. In contrast to taxi drivers, individuals of the general population would not be able to provide a similar expertise, as their knowledge of familiar areas is limited locally to specific areas of London.

Participants:

14 male licensed London taxi drivers were recruited from the taxi rank at Russell Square, London (UK), and all gave written informed consent to participate in the study approved by the ethics committee (ethics number: EP/2018/008). One participant (TD 5, **Supplementary Figure 3.1**) completed the task by indicating the location by boxing the area instead of highlighting area boundaries for the majority of the districts, not allowing to identify perceptual area boundaries. His data was removed, leaving a total of $N = 13$ taxi drivers. Since data was originally intended to provide preliminary insight into the boundary perception of taxi drivers for the analysis of route planning tasks and since the recruitment process proved to be more challenging during winter months, this number of participants was considered acceptable. All taxi drivers reported their age ($M = 45.86$, $SD = 10.77$) and their experience driving a taxi, except for one driver ($M = 9.54$, $SD = 8.77$). The taxi drivers were also asked to indicate areas that they prefer to work in. The reported

areas of preference were areas in Central London: Westend, The City of London, Camden, St Pancras, Chelsea and Fulham.

Material:

A black and white paper map of London was printed in A4 landscape format with a scale of 1:31520 (Ordnance Survey Basemap of the Vector Map District type, supplied by [Digimap](#) by EDINA, University of Edinburgh). The map displayed an area of London ranging from Acton in the west to Limehouse in the east, and from Swiss Cottage in the north to Clapham Junction in the south. Street and area labels were removed to avoid biases in the drawings of areas originating from the positioning of street and area labels in the map.

Since London consists of multiple areas with undefined boundaries (e.g. Bloomsbury), the study focused on prominent, topical districts with distinct functions that were expected to trigger a perception of boundaries. Initially, a list of potential district and area names was derived based on a London A to Z wallpaper map for the area of Central London (i.e. displaying City of Westminster, City of London and central parts of Kensington & Chelsea, Wandsworth, Lambeth, Southwark, Tower Hamlets, Hackney, Islington, Camden). For each district, an online search was carried out to check for official sources that classified potential streets and other network structures as boundaries of those districts and would support a potential boundary perception (for a list of non-exhaustive example sources see **Appendix**). If two or more reliable websites indicated a major consensus on area boundaries (i.e. agreement on most boundaries with only few exceptions, e.g. Whitehall, Southbank), the district or area was included as a task in this study. Additionally included were the extension of Edgware Road to the north and the Westway to the west beyond the Congestion Charge Zone limits (**Figure 3.2c**), as these major roads naturally continue beyond their intersection. Furthermore, the potential western boundary for Central London (i.e. the boundary between the borough of Kensington and Chelsea, and the borough of Hammersmith and Fulham) were added. Finally, geographical structures with boundaries (e.g. major parks) and geographical structures that were expected to be a boundary in themselves (i.e. the River Thames) were included.

The final list of districts and areas with potential boundaries is displayed in **Table 3.1**. A map, summarizing the potential boundaries that taxi drivers were expected to draw, can be found in **Figure 3.2b**.

Procedure:

Taxi drivers received a paper map and were asked to mark the boundaries of each area that they were told by the experimenter. To focus them on generally perceived rather than individually perceived boundaries, they were asked to only mark streets (or other structures, e.g. rivers and train tracks) only if they were sure that nine out of ten other taxi drivers would agree with them on that boundary. *Boundaries* were defined to them as a street (or structure) that enclosed a distinct or area in London or divided two distinct or areas from each other. In this sense, any place or street within an area would be unambiguously divided from a place outside that area through a boundary street (e.g. someone would be considered ‘in Russell Square’ if they were within the area that the roads around the square enclosed). Roads with this function should be marked as boundaries on the map (e.g. all roads around Russell Square that enclose the square).

The experimenter read the list of districts and areas in a random order, which varied across drivers. After the last area was mentioned, they were asked if they perceived any boundary to divide (1) Hammersmith & Fulham from Kensington & Chelsea, (2) Maida Hill from Lisson Grove and (3) the area from Paddington to White City from the north west. Finally, to account for potential areas that might have been excluded by the above criteria, but might be important boundary structures in London, taxi drivers had the chance to add any structures that were not included, but they perceived as boundaries in this context.

Table 3.1. Expected Boundary List

Areal Category	Area Names	Expected Boundary Streets	No. of streets	Exemplary Source¹
Districts Boundary	Mayfair	Park Ln; Piccadilly; Piccadilly Circus; Regent St; Oxford St	5	Google Maps. Mayfair. (2020).
	Soho	Regent St; Piccadilly Circus; Shaftesbury Av; Charing Cross Rd; Oxford St	5	Google Maps. Soho. (2020).
	Belgravia	Knightsbridge; Sloane St; Sloane Sq.; Cliveden Pl; Eaton Gate; Eaton Sq.; Hobart Pl; Grosvenor Pl	8	Google Maps. Belgravia. (2020).
	Leicester Square Area	Haymarket; Cockspur St; Trafalgar Sq.; Charing Cross Rd; Shaftesbury Av; Denman St, Sherwood St; Coventry St	8	File: Leicester Square OSM map.png. (2015, May 13)
	City of London	Petty Wales; Tower Hill; Shorter St; Mansell St; Middlesex St; Brushfield St; Bishopsgate; Worship St; Appold St; Sun St; Wilson St; South Pl; Ropemaker St; Moor Ln; Chiswell St; Whitecross St; Beech St; Golden Ln; Baltic St; Goswell Rd; Charterhouse Sq.; Holborn; High Holborn; Chancery Ln; Strand; Middle Temple Ln; River Thames	27	Google Maps. City of London. (2020).
	South Bank	Lambeth Bridge; Lambeth Rd; Train Tracks to Waterloo; York Rd; Stamford St; Blackfriars Rd; River Thames	7	Our South Bank. (2020).
	Whitehall	Victoria Embankment; Northumberland Av; The Mall; Horse Guards Rd; Great George Street; Bridge St; Whitehall; Parliament St	8	Research Gate. (n.d.).
	Nine Elms	Queenstown Rd; Silverthorn Rd; Nine Elms Rd; River Thames	4	Google Maps. (n.d.). Nine Elms.
Congestion Charge Zone	Vauxhall Bridge Rd; Bressenden Pl; Lower Grosvenor Pl; Grosvenor Pl; Duke of Wellington Pl; Park Ln; Marble Arch; Edgware Rd; Marylebone Rd; Euston Rd; Pentonville Rd; City Rd; Old St; Great Eastern St; Commercial St; White Chapple; Mansell St; Goodman's Yard; Minorities; Tower Bridge Rd; New Kent Rd; Elephant and Castle; Newington Butts; Kennington Ln	24	Wandsworth.gov.uk. (2019, January 11).	
Linear Boundary	Hammersmith & Fulham/ Kensington & Chelsea	West Cross Route; Train Tracks: Imperial Wharf – Shepherd's Bush	NA	The Royal Borough of Kensington and Chelsea. (n.d.).
	Maida Hill/ Lisson Grove	Edgware Road Continued north	1	Continuation of Congestion Charge Zone to north
	White City, Paddington/ North West	Westway	1	Continuation of Congestion Charge Zone to west
Park Boundary	Regent's Park	Ulster Terrace; Outer Circle; Gloucester Gate; Prince Albert Rd; Park Rd; Hannover Gate; Outer Circle	7	Mappery. (2009, June 30).
	Hyde Park	Kensington Rd (Kensington Gore); Knightsbridge; Park Ln; Marble Arch; Hyde Park Pl; Bayswater Rd; Kensington Palace Gardens	7	Mappery. (2004, March).
	Battersea Park	Albert Bridge Rd; Prince of Wales Dr; Queenstown Rd; River Thames	4	Friends of Battersea Park. (n.d.).
River	Thames		NA	

¹List with further sources can be found in **Appendix**

3.4. Results

In this study licensed London taxi drivers drew the boundaries of London districts on a paper map. With these drawings, the aim was to gain a better understanding of area boundaries of the street network in Central London as perceived by expert navigators, such as taxi drivers, who know the whole street network of London extremely well. The analysis of the boundary drawings on paper maps was carried out in two layers: An initial understanding was gained from the overlay of all map drawings, showing all boundaries that were perceived across drivers. An overlaid mapping of boundaries with above average agreement (50%-100%) was created and agreement rates were identified across all drawings and used for a comparison of above average agreement (50%-100%) with expected boundaries.

Overlaid Mapping of all Drawings

An overlaid mapping of all boundary drawings was used to identify differences in agreement that indicate how manifested a boundary is across individuals. For this overlaid mapping, the individual drawings (**Figure 3.3a**) were each digitised (**Figure 3.3b**) using GeoJSON ([GeoJSON, n.d.](#)), an open standard format that allows a representation of geographical features as well as non-spatial attributes based on JavaScript Object Notation (JSON). An overlay of the digitised boundary maps was then created with Mapbox (**Figure 3.3c**), a platform that supports customised processing and design of geospatial maps ([Mapbox, 2020](#)). The boundaries were displayed with increased transparency to create higher opacity for boundaries that are overlaid with higher frequency. The resulting map that contained all drawings (**Figure 3.3c**, for an interactive map, see [Salhab, 2020](#)) was then also used in subsequent analysis to identify differences between areas with varying levels of agreement.

The map showed a good agreement for the major Parks, Mayfair, Soho, the Congestion Charge Zone, Westway, Edgware Road extended north and the River Thames. Parts of Belgravia, Whitehall and the Boundary between Hammersmith and Kensington also indicated increased agreement across drivers, but also highlighted some ambiguity for individual boundaries. More ambiguous boundaries appeared to be in areas around Leicester Square (**Figure 3.3e**), Nine Elms, South Bank and the City of London (**Figure 3.3d**).



Figure 3.3. Overlay of boundaries. The original paper drawings (a) were digitised in [geoJSON](#) (b). A layover of all drawings (c) was created. Lines with higher opacity, e.g. boundaries around Mayfair and Soho (e), indicate a higher agreement across drivers on a boundary street than for streets with low opacity, e.g. City of London (d). Sources: (a) [Digimaps - Edina](#); (b) [geoJSON](#); (c-e) Overlaid mapping created by Melda Salhab

Overlay of Major Boundaries

Since this study aimed to understand the emerging pattern of perceived boundaries for the majority of drivers (more than 50% consensus), streets with an agreement of at least two drivers were transcribed. These created a frequency count to determine consensus across all boundary drawings. Streets with an increased frequency count (>50%) and a

Table 3.2. Consensus of boundary drawings across licensed London taxi drivers.

Consensus Level	Area Category	Area Names	Overall Consensus	
High (>80%)	Park Boundary	Regent's Park	95.38%	
		Battersea Park	90.38%	
		Hyde Park	88.46%	
	Districts Boundary	Mayfair	100%	
		Soho	93.85%	
		Belgravia	88.46%	
		Congestion Charge Zone north ¹ (total)	85.71% (65.23%)	
		City of London Riverside ²	80.77%	
Increased (>50%)	Districts Boundary	South Bank	67.69%	
		Whitehall	63.08%	
	Linear Boundaries	Edgware Rd Continued	69.23%	
		Hammersmith – Kensington ³ (total)	65.38% (50.77)	
		Westway	61.54%	
			Nine Elms Lane	61.54%
		River	River Thames	61.54%
Low (<50%)	District Boundaries	Nine Elms	44.61%	
		Leicester Square Area	39.56%	
		Congestion Charge Zone south ⁴	39.16%	
			City of London (total)	no consensus on most boundaries

¹all streets north of the River Thames from Victoria St (south west) to Commercial Street (east); cf. Figure

²only refers to Upper Thames St and Lower Thames St

³Holland Rd and Warwick Rd only

⁴all remaining streets from the Congestion Charge Zone from Whitechapel high St (east) to Vauxhall Bridge Road (south west)

high frequency count (>80%) were then cumulatively mapped to identify streets had a high likelihood of being perceived as a boundary and potential features of the street network linked to this perception.

Consensus

For each London district with expected boundaries as listed in **Table 3.1**, the streets that were identified by at least two taxi drivers were transcribed and the frequency by which each street was identified as a boundary across all drawings was counted. The overall consensus was calculated in percentage for each district separately and is listed in **Table 3.2**. Three levels of agreement were distinguished to allow to understand general tendencies: *low* (< 50%), *increased* (>50%, but less than 80%) and *high consensus* (>80%). On the overlaid map that contained all boundary data (**Figure 3.4a**), increased consensus (**Figure 3.4b**) and 100% consensus (**Figure 3.4c**) were then visualised to indicate the two extreme levels of boundary agreement rates.

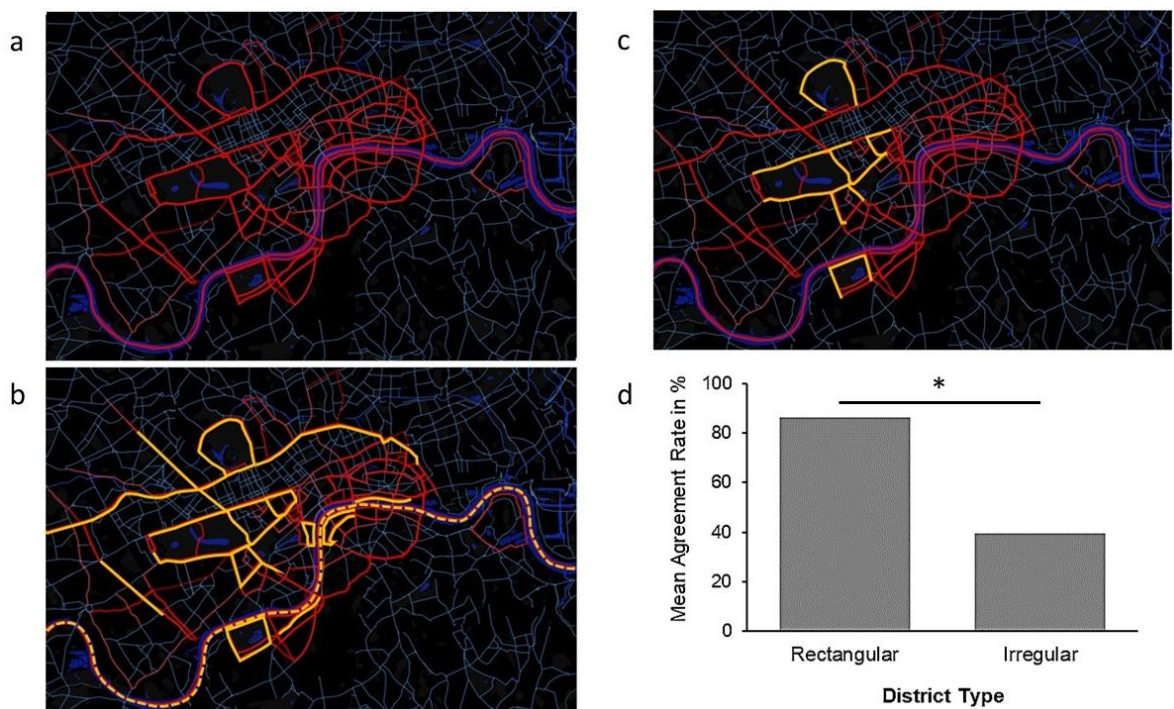


Figure 3.4. Agreement rates across boundary drawings. The overlay of all boundary drawing indicates areas of different rates of agreement. (a) All boundaries that were overlaid and highlighted in red. (b) Boundaries where the agreement was higher than 50% across drawings highlighted in yellow. (c) Individual streets of regions that were identified as boundaries with 100% of agreement across taxi drivers highlighted in yellow. (d) Comparison of mean agreement rates for districts with almost rectangular (Soho, Mayfair, Belgravia, Whitehall) and irregular shape (Southbank, Leicester Square, Nine Elms, City of London) show significantly higher agreement ($t(6) = 3.1, p < .05$) for almost rectangularly shaped districts (86%) than for irregularly shaped districts (39%). Map source: Overlaid mapping created by Melda Salhab

Boundaries with *high consensus* included the three major parks with consensus ranging from 88.46% (Hyde Park) to 95.38% (Regent's Park) and district boundaries for Mayfair and Soho above 90%, Belgravia (88.46%), the northern parts of the Congestion Charge Zone between Victoria Street and Commercial Street (85.71%) and the southern boundary along the river for the City of London (80.77%).

Increased consensus was found for the two districts of South Bank (67.69%) and Whitehall (63.08%). All linear boundaries (the continuation of Edgware Road northbound, the division of Hammersmith and Kensington, the Westway and Nine Elms) and the River Thames ranged between 69.23% at the higher end and 61.54% at the lower end.

Ambiguous boundaries with *low consensus* (<50%) were below 45% of agreement. These areas included Nine Elms, Leicester Square, the remaining part of the Congestion Charge Zone as well as the City of London, and all other remaining boundaries from the complete overlaid mapping.

A comparison of mean agreement rates of districts with a near rectangular shape and districts of irregular shape was carried out (**Figure 3.4d**). Here, Soho, Mayfair, Belgravia and Whitehall were classified as districts with an almost rectangular outline, whereas Southbank, Leicester Square, Nine Elms and the City of London were contained in the group of irregular shaped districts. Not included in this comparison were the major parks as these were conceptually different due to their greenspace character, the Congestion charge Zone due to the dual shape (near rectangular in west and north, but round in the east and south), as well as other linear boundaries. Mean agreement rates were significantly higher ($t(6) = 3.1, p < .05$) for almost rectangular districts ($M = 86, SD = 16$) than for irregular districts ($M = 39, SD = 25$).

Perceived Boundaries and Expected Boundaries

The impact of culturally defined boundaries for districts was studied by comparing the list of expected boundaries to the boundaries with high or increased consensus (**Figure 3.5**). This comparison indicates an overlap for Hyde Park, Regent's Park, Mayfair, Soho, the Westway, the extension of Edgware Road towards the north, and the River Thames. A partial match was obtained for Battersea Park (except for the Prince of Wales Drive), Belgravia (except the boundary between Sloane Square and Grosvenor Place), South Bank (except for the extension along the River Thames), the riverside area of Whitehall,

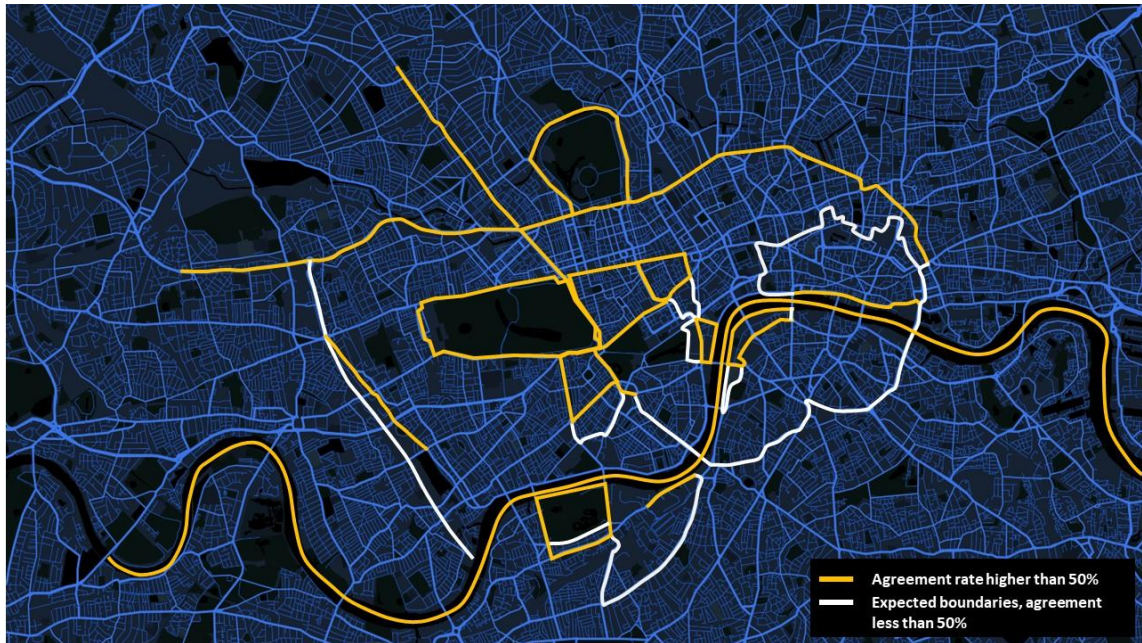


Figure 3.5. Comparison of expected and perceived boundaries. The agreement rate on drawn boundaries that surpassed 50% across taxi drivers was used to highlight above average agreement on perceived boundary streets. Yellow: agreement across drivers above average. White: Expected boundaries, that did not surpass average agreement level (50%). Map source: [Mapbox](#)

the riverside boundary of the City of London and the northern boundaries of the Congestion Charge Zone. Deviations were found for the boundary between Hammersmith and Kensington (streets parallel to the train tracks) and Nine Elms (Nine Elms Lane). The area of Leicester Square, the majority of the City of London, as well as the southern part of the Congestion Charge Zone had low or hardly any overlap with expected boundaries due to low agreement across drivers.

3.5. Discussion

To study if humans mentally segregate an environment through geographical boundaries, data was collected from boundary drawings on maps by London taxi drivers. Taxi drivers were chosen, because they are trained on the Knowledge of London (see **Chapter 2**), which requires them to learn the entire London street network to flexibly navigate between places without consulting additional navigation aids. Years of training and extensive experience driving a taxi ensure exceptional familiarity within streets and districts in the six-mile area around Charing Cross station (see **Chapter 2**) and allows for testing of perceptual street-network boundaries of districts and regions that the general population would not be able to display. Based on this profound knowledge, data from boundary drawings on maps provided initial insight into the mental representation and a potential segregation of a complex, urban space. Results highlight in particular how

mental representations of spatial structures can vary between individuals and that often clearly defined boundary structures based on historical records and legislation might not be perceived as such mentally. In the following, these results will be considered in the light of general, geographical and behavioural findings. Conceptual limitations, such as a small sample size, a male group of participants and recruitment from a particular location, will also be discussed.

General Observations

In this study, mental representations of street network related boundaries were assessed through boundary drawings on paper maps by taxi drivers. An overlay of these drawings (**Figure 3.3**) indicated areas with highly agreed boundaries, such as Mayfair or Soho, as well as areas with hardly any agreement on one particular boundary, such as Leicester Square and the City of London. Agreement rates on whether a street was a boundary or not varied even for the series of streets that enclosed individual regions (e.g. South Bank) or formed linearly separating boundaries (e.g. Westway to City Rd). However, geographical or conceptual spatial boundaries and structures (e.g. [Lynch, 1960](#)) in general often rely on precise definitions. In this study, there is evidence that even such obvious geographical structures not always reflect the same clarity on a perceptual level by which they are defined. For instance, the River Thames only reached agreement rates at the bottom end of what was categorically considered as a boundary in this study (see **Table 3.2**). Such a discrepancy between geographical or conceptual definitions and perception might pose a problem for many spatial studies on navigation as they might wrongly assume a clear perception of boundaries where disagreement of boundaries might prevail. Thus, studies on navigation in a real-world environment will have to take into account how such discrepancies in perceptual spatial boundaries can impact on human navigation (cf. **Chapter 4**). Additionally, the low agreement rates for the River Thames might also be explained through this conceptual difference between street network boundaries and geographical structures that form boundaries. For the purpose of this study, boundaries were defined as specific streets of the street network that segregate particular areas or districts from each other and could be used for route planning purposes. In contrast, other definitions of boundaries (e.g. [Lynch, 1960](#)) regarding survey knowledge of individuals also involve geographical structures, such as waterways, trainlines, or concrete barriers that similarly separate areas, but are not necessarily used for travelling purposes. The

River Thames, would thus fall under the latter definition and not entirely be in line with the current definition of a street-network boundary that can be travelled on. However, it was included as a prominent boundary that indirectly affects the street network, as it separates South London from the rest of London, which are connected via bridges, special and often prominent forms of street network structures.

A challenging question in this context is to identify and predict which spatial structures ultimately qualify as boundaries with a high agreement and which do not. In general, mentally perceived street-network boundaries, in contrast to their conceptual or geographical definition, show a range of deviations and inconsistencies in which streets are precepted as boundaries by individuals. An entire agreement on one particular street was rarely given. Instead, the mental perception of boundaries was best described through agreement rates rather than a binary classification into mental ‘boundaries’ and ‘non-boundaries’, due to these inconsistencies in perception. Still, to allow for categorical references, low (<50%), increased (>50%) and high (>80%) agreement rates were used to classify different levels of agreement. These only aimed to explore general tendencies to gain an initial understanding of prominent boundaries in the London street network and contribute to a potential segregation of the environment. Even though the collected data is preliminary, it already highlights interesting tendencies that can be used for subsequent studies to tests if districts and regions are bound by boundaries or if boundaries divide areas from another as discussed in the following.

Initial expectations of potential perceptual boundaries were based on geographical structures, such as parks or the River Thames, as well as prominent, topically distinct districts, such as Soho or Mayfair that are enclosed by a regular street network structure (see also **Table 3.1**). These expectations were met in general as street network boundaries for the three major Parks, the River Thames, several districts (e.g. Soho, Mayfair and Belgravia) and areas (e.g. Congestion Charge Zone north of the river), as well as some linearly separating boundaries (e.g. Westway, Edgware Road northern extension) were identified. Other areas, such as the City of London, Leicester Square, Nine Elms or the Congestion Charge Zone south of the River Thames were not found to have perceptual street network related boundaries despite their popularity or topical distinctness. Here, additional factors impact on whether spatial structures are mentally perceived as boundaries or not.

Popularity and topical distinctness alone are not sufficient for such a perception, as the areas of Leicester Square or the City of London show. The regularity of the street network,

i.e. long straight streets, or near rectangular structure of districts seems to play an important role as well. Streets that are linearly linked to separate areas (e.g. Westway, Marylebone Rd, Euston Rd, Pentonville Rd, City Rd, Old St) or enclose areas in an almost rectangular shape (e.g. Soho and Mayfair) are more likely to be perceived as boundaries than non-linear roads (e.g. Charing Cross Rd in the east of Leicester Square) or irregularly shaped boundaries, such as the boundaries of the City of London.

Perceived boundaries also coincide with main roads (see **Figure 3.2**), increasing the likelihood of a boundary being an important street network connection between places. Streets that are not main roads, but conceptual boundaries, such as the northern outline of the City of London, were less likely to be perceived as boundaries in this study. Furthermore, not all major roads are perceptual boundaries, despite evidence from Parisian taxi drivers ([Pailhous, 1969](#)) who were found to represent the street network in two layers. However, degrees of perception of the main road network that could highlight more or less perceptible network structures were not studied. In this context, spatial analysis of street network properties, as through space syntax, could provide important insight how centrality measure impact mental representations of spaces. Due to time constraints these were not included in the current analysis, but will be considered for future publications.

Additionally, distance to the centre of London also seems to impact on agreement rates. Districts with high agreement rates include Soho, Mayfair and Belgravia, located centrally, within or near the Congestion Charge Zone, which is also a more prominent boundary north of the River Thames than south (see **Figure 3.4**). Increased agreement rates were found for partial boundaries of the central London districts of Whitehall and South Bank along the River Thames. South of the River Thames, Nine Elms and the southern boundaries of the Congestion Charge Zone, despite being straight and regular, had low agreement rates. However, in this context, tightly linked to proximity is familiarity of taxi drivers with central London areas. As drivers reported areas of preference being in West and Central London, which are areas where boundary agreement rates were increased or high, their familiarity with areas south of the River Thames might be limited and impact boundary perceptions and agreement rates in those areas.

Interestingly the River Thames, a prominent geographical landmark running through London, was not identified as a boundary with high agreement rates. Contrary to this expectation, only about 62% of drivers perceived it as a separating structure of south London and the rest, rendering it categorically a boundary with one of the lowest

agreement rates that surpassed the chance level of 50%. However, the River Thames seems to be special in this context as for districts and regions, taxi drivers were expected to indicate bounding streets, but for the Thames it was the river itself, rather than streets that was expected to have a boundary effect. This conceptual difference might have affected responses. Support for this could be indications of the City of London riverside boundary that runs along the river. Furthermore, it can be argued that the River Thames itself does not necessarily separate prominent, confined and topically distinct areas, as for Soho. Instead, on a larger scale, districts along the river might fade into each other or even span across the river as touristic areas of Central London not only include areas north of the River Thames, but also stretch from Waterloo along South Bank to Tower Bridge at the southern bank of the River Thames. Such concepts on a higher level might interfere and explain deviations from the conceptual understanding of boundaries on a smaller, more locally perceived scale as with specific districts and areas.

Finally, it is interesting to note hardly any taxi drivers indicated additional structures that they would perceive as boundaries in this context. Where taxi drivers did, the perceived streets were not agreed on by other drivers (e.g. Camden, King's Cross and Greenwich). These regions, similar to the City of London and similar areas with diffused boundaries across the street network, had individually perceived boundaries.

Boundaries and Urban Geography

From a geographical point of view, these findings are also in line with previous approaches that studied for instance how individuals mentally represented cities through paths, edges, districts, nodes and landmarks (Lynch, 1960). In his studies, Lynch (1960) highlighted several properties of streets, such as width, distinctiveness, continuity, directionality or importance in terms of being a major path, that were central for its identification and can also be attributed to boundary properties, such as linearity or almost rectangularity, topical segregation of distinct areas, high likelihood of being a major roads. Similarly, edges, defined by Lynch (1960) as boundaries between different types of areas, such as waterways, were found to be important spatial structures of the mental representation of individuals. Parallels can be drawn between edges in Lynch's study (1960) and the street network boundaries of parks, or the River Thames itself. Additionally, Lynch (1960) also points out a gradual change of path properties along the paths that also cause a gradual change in its perception. Changes in boundary agreement

along linear sequences of boundary streets could also relate back to such a topological gradient along those boundaries.

Retrospectively seen, previous approaches of segregating an urban environment based on street network properties (e.g. [Filomena, Verstegen & Manley, 2019](#)) have not matched perceptual findings of this study and are not reflective of how humans ultimately perceive their environment. These approaches seem too fine grained for human perception and do not include additional perceptual or conceptual factors such as popularity, topical distinctness or regularity of the street network that were found to drive human perception. More importance factors include if streets can be classified as main roads ([Pailhous, 1969](#)). Even though, not all main roads were perceived as boundary roads, those which were boundaries were main roads (see **Figure 3.2**). Since main roads are often important arteries and overlap with critical streets (cf. [Working papers Series, 2020](#)) of the street network, spatial analysis as by space syntax could provide further insight in terms of spatial properties. Due to time constraints, such an analysis went beyond the scope of the current project.

Boundaries and Behavioural Science

As boundaries were found to more likely emerge around prominent, topically distinct areas, surrounded by main roads with a regular, linear shape, they seem to be in line with findings on distortion effects of mental representations of space (e.g. [Costa & Bonetti, 2018](#); [Tversky, 1981](#); [Tversky 1992](#); [Okabayashi & Glynn, 1984](#); [Stevens & Coupe, 1978](#); [Milgram 1976](#); [Bomba & Siqueland, 1983](#)). In particular, geographical shapes of irregular borders are often simplified and represented as straight lines ([Milgram 1976](#); [Tversky, 1981](#)) and angular irregularities in the street network often aligned in a parallel, grid-like shape (e.g. [Byrne, 1978](#)). Such tendencies towards simplification might ultimately also determine which spatial structures are more likely to be remembered ([Lynch, 1960](#)) and thus recalled and identified as potential boundaries.

In contrast to the spatial boundaries as defined in this or other studies (e.g. [Lynch, 1960](#)), spatial boundaries have been conceptualised in wider terms as well. Turns ([Brunec, Ozubko, Ander, Guo, Moscovitch & Barense, 2020](#)) or doorways in an indoors setting ([Robinson, 2020](#)) seem to form a mental barrier that impacted spatial memory. Whilst doorways, similar to the current study, establish a spatial boundary that separates two distinct spaces (i.e. rooms), they are more obvious structures than streets that conceptually

segregate a complex outdoor environment. Turns in contrast, are less obvious boundaries and do not fit the concept of spatial boundaries as assumed in this study. Instead of marking spatial places where spatial regions differ, turns as studied by Brunec and colleagues (2020) mark a particular event in a route that leads to a segmentation of a mental representation and thus impacts spatial memory recall.

Other studies that rely on spatial segmentation or hierarchical representations of the environment (e.g. [Wiener & Mallot, 2009](#); [Wiener, Schnee & Mallot, 2004](#); [Schick, Halfmann, Hardiess, Hamm & Mallot, 2019](#); [Büchner, Hölscher & Strube, 2007](#)) created those artificially through themed areas, such as visually cued areas ([Wiener & Mallot, 2009](#); [Wiener, Schnee & Mallot, 2004](#)) and language cues ([Schick, Halfmann, Hardiess, Hamm & Mallot, 2019](#)). Here, boundaries were not explicitly studied or perceptible, but implicitly included as transitions between areas occurred. However, in real-world navigation, boundary streets can impact how individuals make use of their mental representations to travel an environment. Route planning and wayfinding can be affected by such structures and are thus important to be considered (See **Chapter 4**).

Conceptual Limitations

This study was carried out to provide an initial understanding of a potential mental segregation of London to study hierarchical route planning (see **Chapter 4**). Therefore, conceptual limitations such as a small sample size (N=13 taxi drivers), the testing of male subjects and a focus on recruitment at a particular location should be taken into consideration in future studies. Data collected with a larger sample and testing across various locations at London taxi ranks or through online experiments to gain a more accurate understanding could easily be addressed in the future. Time constraints during the recruitment process did not allow to address these in the current, preliminary study. It will also be more difficult to test a gender balanced group of taxi drivers, as taxi drivers are predominantly male.

Further consideration should also be given to the design of the study. Here specific places were chosen because of their topology (e.g. major parks, the River Thames), functionality (e.g. the Congestion Charge Zone, the City of London), prominence, popularity and topical distinctiveness (e.g. Soho, Mayfair, South Bank) and taxi drivers were asked to draw the boundaries of these districts or regions into a map. Alternative designs might take a different approach. Instead, subjects could be asked to indicate any

street network structures they perceive as boundaries in London on a general all London map, or only focusing on main roads in line with findings with Parisian taxi drivers ([Pailhous, 1969](#)) and the current study. However, these approaches might leave room for interpretation amongst taxi drivers of what is considered conceptually as a street network boundary as defined in this context as studies on neighbourhoods with locals show (cf. [Stansfeld, 2019](#)). Moreover, the chance to indicate further structures on the map at the end of the study only seemed to prompt individually perceived boundaries rather than general tendencies (e.g. Camden, King's Cross and Greenwich).

Other methodological approaches could consider testing all possible districts and areas instead of a subset, which would be more time consuming and thus might become more demotivating as taxi drivers might have to reject many areas that don't have perceptual boundaries. Alternatively, a boundary recognition test that prompts taxi drivers to identify districts only based on their boundaries (e.g. by councils) could provide a more efficient method of testing area and district boundaries. However, individual differences in perception across drivers would get lost. For instance, the area of Leicester square or the City of London might be more likely to be recognised as such, but variations on area boundaries would not be detected.

Generalising for the General Population

It also can be argued that findings from London taxi drivers cannot be generalised easily. As found in **Section 2.4** taxi drivers are trained to develop an elaborate and accurate mental representation of the environment, that can hardly be found within any other group of the general population. Here, a fragmented and potentially greatly distorted mental representation of the environment is prevalent and boundaries might be weighted differently. For instance, prominent geographical structures, such as the River Thames, might carry more weight. Furthermore, perception of boundaries in a confined environment, such as a neighbourhood (cf. [Stansfeld, 2019](#)), might be more prominent in individual perception (even if not agreed on) and impact their navigation differently than a large-scale mental representation does for taxi drivers.

On the other hand, such a fragmented knowledge in other, more prominent and distinct areas of London, such as Soho, might match more closely and findings from taxi drivers' perception of boundaries could reflect general tendencies (cf. [Lynch, 1960](#)). Testing such

overlaps with the general population were beyond the scope of this project, but should be explored in the future in order to gain a more detailed knowledge.

Conclusion

The current study, despite its preliminary approach, highlighted several interesting points about perceptual boundaries of the street network in mental representations of urban environments. In general, these boundaries were best described through agreement rates as they varied across taxi drivers in their strength to which they were perceived. This stands in contrast to general tendencies that precisely define spatial boundaries based on geographical or conceptual properties. Areas with perceived boundaries were found to share common properties, such as being prominent and distinct from their surrounding areas, but also have a regular, linear or almost rectangular outline that is more memorable. These findings will ultimately allow to gain a more profound insight into route planning behaviour.

4. ROUTE PLANNING EVIDENCE OF HIERARCHICAL REPRESENTATIONS OF LONDON

4.1. Abstract

The impact of a hierarchically structured environment on route planning and spatial navigation has been widely studied in many obviously defined hierarchical environments in a virtual setting. Evidence from a real-world, urban environment is still missing. Here, London taxi drivers, who are capable of planning and recalling routes by naming individual streets and giving precise travelling instructions, were tested on several route planning tasks across London. Their audio recorded route recalls were transcribed together with their response times between individual streets. These were then related to spatial structures of the environment to understand how these structures impact route planning. Results from a linear mixed model analysis indicate that the Euclidean distance to the goal has little bearing, whereas a range of other variables impact route planning. These include agreement ratings of mentally represented street network boundaries and other street network related features, such as turning actions and road types. These findings provide evidence for a hierarchical representation of real-world spaces and its exploitation during route planning.

4.2. Introduction

On a daily basis, humans travel between multiple places in a city and reach a destination only based on their knowledge of the environment. Often this spatial knowledge of the surrounding environment is developed through frequent travelling and experience. It includes knowledge of the street network as well as places located within this street network, and it enables individuals to plan a route from their best friend's home to their favourite restaurant. In a small-scale environment that consists of a small number of streets, such as villages or towns, near flawless spatial memories of the environment can easily be obtained and used to make plans. However, in large-scale, complex cities, such as London (UK), where the street network consists of about 53,000 streets ([OS MasterMap Integrated Transport Network, 2018](#)), using this method to plan and compare several routes between the two extreme ends of the environment will appear extremely challenging and time-consuming: From a perfect navigator, who is planning to go from Shepherd's Bush (West London) to Canary Wharf (East London) and aware of the entire

London street network, it would require an enormous amount of spatial memory and processing skills if their information of the entire street network had to be processed. Therefore, it seems unlikely that humans plan, hold information and choose from not only one, but several potential options to find a solution for their travel plans. Even with long routes, such as from Shepherd's Bush to Canary Wharf, humans are capable of forming such plans in a considerably short amount of time, which would render time-consuming route planning strategies that involve consideration of the entire environment extremely unlikely. Instead, hierarchically structured representations have been widely discussed in many experimental settings containing virtual environments and small-scale, real-world spaces (e.g. [Wiener & Mallot, 2009](#); [Wiener, Schnee & Mallot, 2004](#); [Schick, Halfmann, Hardiess, Hamm & Mallot, 2019](#); [Büchner, Hölscher & Strube, 2007](#); [Badre, Kayser & D'Esposito, 2010](#)). Hierarchies allow to store and exploit complex information, such as London's street network, through meaningfully grouped chunks of street network regions instead of having to evaluate numerous individual streets. However, it remains unclear how humans process and exploit such hierarchies and other spatial structures of a real-world environment as large as London's street network to form a route plan. In the following computational and experimental ideas are explored and a real-world experiment to study how a group of navigation experts plans routes in London, UK is presented.

Computational Approaches

Machine learning and computational neuroscience have suggested a range of approaches to model such planning behaviour. Traditional models often use a tree-search that represent all potential options at each stage as branches of a tree and specific plans are sequences along those branches. For instance, the most basic decision tree is a two-branch tree (see **Figure 4.1a**) that only allows for decisions between two options at each step and a specific plan forms an entire trajectory (**Figure 4.1a**). More complex trees allow for more options at branches, thus increasing the breadth of the tree, or require more steps as the number of levels increase and hereby add to the depth of the tree. Computationally, tree-search algorithms can work in multiple ways by comparing alternatives (breadth-first) at each step or entire sequences of steps (depth-first) to describe options that lead to a particular result (e.g. [Streeter & Vitello, 1986](#); [Elliott & Lesk, 1982](#); [Miller & Venditto, 2020](#)). More common approaches involve Monte Carlo

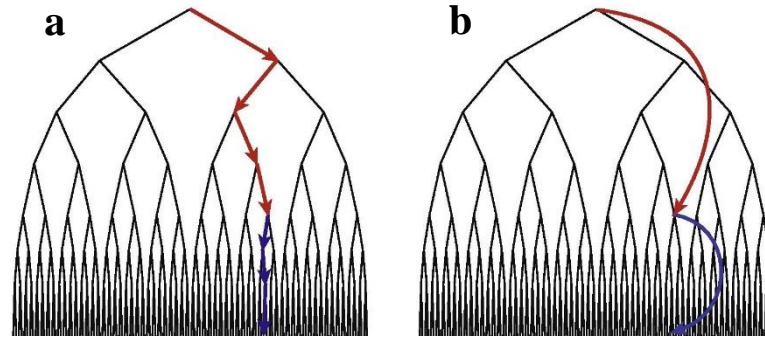


Figure 4.1. Tree-search in a two-branch tree. Schematic illustrations of decision sequences are often represented through decision trees (a). At each branch of the tree, a new decision is required (arrows). This sequence of decisions ultimately forms a trajectory along the branches of the tree (sequence of arrows) to a particular goal. Route planning options through a street network can similarly be represented where individual branches reflect streets and trajectories particular routes through the street network. In a hierarchical representation, routes will be broken down into sequences of shorter sections (red and blue) of the trajectory (b). Adapted from [Botvinick, Niv & Barto, 2009](#)

tree-searches that randomly sample trajectories (e.g. [Browne, Powley, Whitehouse, Lucas, Cowling, Rohlfshagen, Tavener, Perez, Samothrakis, Colton, 2012](#)). Other algorithms make use of reinforcement-based strategies that rely on model-free and model-based strategies. These models assign transition probabilities to different states (i.e. locations) of the space that is being travelled (i.e. model-free) or encode an entire model of the external environment (model-based) to describe the overall likelihood with which a route is chosen (e.g. [O’Doherty, Lee & McNamee, 2015](#); [Botvinick, Niv & Barto, 2009](#); [Daw, Gershman, Seymour, Dayan & Dolan, 2011](#); [Huys, Eshel, Onions, Sheridan, Dayan & Roiser, 2012](#); [Gershman, Horvitz, Tenenbaum, 2015](#); [Miller & Venditto, 2020](#); [de Cothi, 2020](#)). For small-scale and virtual reality environments these models have closely described human and animal behaviour (e.g. [de Cothi, 2020](#); [Daw, Gershman, Seymour, Dayan & Dolan, 2011](#); [Streeter & Vitello, 1986](#); [Elliott & Lesk, 1982](#); [Miller & Venditto, 2020](#)). However, they fail to explain route planning behaviour in large-scale environments due to the enormous computational demand, even though attempts to eliminate unfavourable options have been made (e.g. [Huys, Eshel, Onions, Sheridan, Dayan & Roiser, 2012](#); [Milford & Wyeth, 2007](#)). Considering London’s 53,000 streets, a basic tree search algorithm for a route consisting of 30 streets (decision points) in a basic two-branch tree, would require a computation of $2^{30} \approx 1$ billion potential sequences (see [Huys, Eshel, Onions, Sheridan, Dayan & Roiser, 2012](#)). However, humans are capable of finding a route across an even larger street network with more options remarkably quickly, rendering such computations unlikely.

To reduce the computational demand of operations, hierarchical approaches have been introduced (e.g. [McNamee, Wolpert & Lengyel, 2016](#); [O’Doherty, Lee & McNamee, 2015](#); [Botvinick, Niv & Barto, 2009](#); [Tomov, Yagati, Kumar, Yang & Gershman, 2020](#); [Bast, Delling, Goldberg, Muller-Hannemann, Pajor, Sanders, Wagner & Werneck, 2015](#)). In contrast to conventional approaches, hierarchical models, such as the normative model of efficient state-space modularisations ([McNamee, Wolpert and Lengyel, 2016](#)), segregate the global space efficiently and represent it through smaller, distinct areas (i.e. ‘*modules*’) that contain local information about specific places (i.e. ‘*states*’). These models exploit that computations are restricted to a subset of modules (and states) instead of the entire environment. In particular, on a global level (e.g. London, UK), route planning is carried out across modules (e.g. London districts, such as Soho, Mayfair, Covent Garden, etc.) to select relevant and eliminate irrelevant modules. Locally, i.e. within each module (e.g. Soho), a particular route is planned across each module to its boundaries using the limited number of states available (e.g. from Shaftesbury Avenue to Argyll Street) and ultimately resulting in multiple sequences of shorter routes (see **Figure 4.1b**). On a small-scale, these models have been tested and reflect a good fit with real-world data that was collected whilst studying mental walks of a university campus at the University of Toronto and route planning tasks in the London district of Soho ([McNamee, Wolpert and Lengyel, 2016](#)).

Spatial Experiments

Hierarchical planning has been in the focus of a range of experimental settings, with a variety of approaches to study the impact of hierarchical structures, such as problem solving games ([Ward & Allport, 1997](#); [Knoblock, 1990](#)), regionalised virtual environments (e.g. [Wiener & Mallot, 2009](#); [Wiener, Schnee & Mallot, 2004](#)), the linguistic impact of semantics and preferences for regional crossings ([Schick, Halfmann, Hardiess, Hamm & Mallot, 2019](#); [Schick, 2018](#)), map configurations of categorical object features (e.g. [Wiener, Ehbauer & Mallot, 2009](#); [Hommel, Gehrke & Knuf, 2000](#); [Solway, Diuk, Cordova, Yee, Barto, Niv & Botvinick, 2014](#)) or a virtual subway network ([Balaguer, Spiers, Hassabis & Summerfield, 2016](#)). Evidence from these studies suggests not only a regionalised representation of a fictional environment, but also that humans exploit levels of hierarchies to minimise planning demands ([Balaguer, Spiers, Hassabis & Summerfield, 2016](#); [Schick, Halfmann, Hardiess, Hamm & Mallot, 2019](#)). In

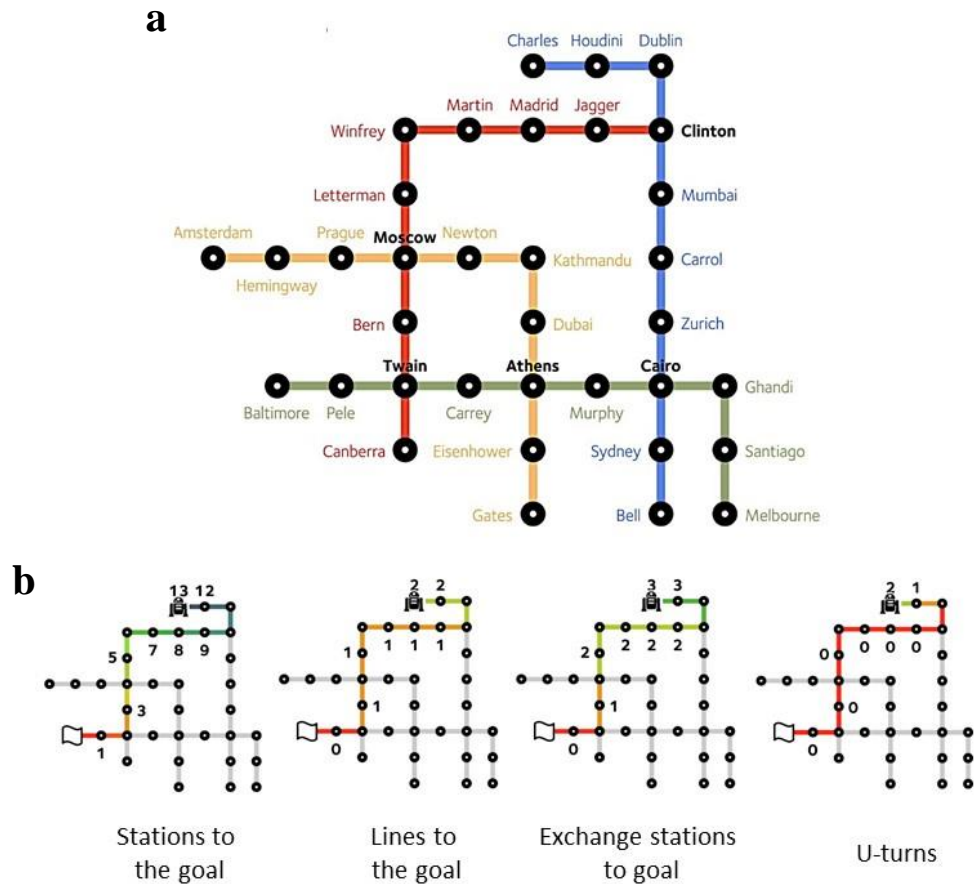


Figure 4.2. Hierarchies in a transportation network. In transportation networks, a hierarchical structure is often naturally imposed through different transportation liens that connect stations. This was tested by Balaguer and colleagues (2016) through a virtual subway network that participants navigated (a). Different factors, indicative of hierarchical planning, were tested (d), including stations, lines and exchange stations to the goal, to differentiate between a flat and a hierarchical representation. Adapted from Balaguer, Spiers, Hassabis & Summerfield, 2016

particular, Balaguer and colleagues (2016) asked individuals to plan routes through a virtual transportation network (Figure 4.2). Here, a hierarchical structure was imposed in form of different subway lines and a tested through several route properties. These included the number of lines, stations and exchange stations to the goal, as well as U-turn events (Figure 4.2). Behavioural results indicated amongst others a contextual impact of these transportation lines over an unclustered, flat representation of individual states on the planning behaviour in transportation networks, pointing towards a hierarchically layered representation of the virtual environment. Such a hierarchical representation of the transportation network, in contrast to ‘flat’ representations of independently stored stations, allows humans at each step to focus their planning on a subset of steps rather than the entire environment.

Real-world support for hierarchically structured planning of routes is still missing, despite indicators of Parisian taxi drivers, who were found to represent the street network through a higher level of major roads and a lower level of minor roads (Pailhous, 1969).

Here, experience drives the efficiency with which routes are chosen, as more experienced drivers exploit the secondary street network more efficiently than novice drivers, who mainly restrict their plans to the major network. However, this effect of hierarchical layering based on road types can be explained through the restriction of Parisian taxi driver training to major roads ([Prefecture de Police, Demarches & Services, 2002](#)). In contrast to road types, evidence of a hierarchical representation through regions was found in the faster recall of spatially closer neighbourhoods by Pittsburgh taxi drivers and distance estimations that indicated greater overestimation of distances when two reference places were separated by boundaries of neighbourhoods ([Chase, 1983](#)). Such systematic variations of response times and distance estimations of places within neighbourhoods, or neighbourhoods that are locally closer to each other, point towards a hierarchical representation of the urban environment ([Chase, 1983](#)). However, the same study also tested route planning differences of taxi drivers' in relation to the primary and secondary street network. Drivers were asked to describe the shortest route from an origin to a destination. Whilst novices mainly relied on the primary street network, which they were trained on, more experienced drivers, exploited the secondary street network more efficiently due to their driving experience in the entire street network. However, these results rather indicated an experience effect than an impact of a hierarchically structured environment. Still, this study only tested planned route with respect to road types rather than other cognitive indicators for hierarchical planning, such as response times related to individually named streets. Further evidence for hierarchical planning could also be found in the aforementioned mental simulations of real-world routes (e.g. [Bonasia, Blommestejn & Moscovitch, 2015](#); [Arnold, Iaria & Ekstrom, 2016](#)). These highlight clustering of spatial areas and temporally compressed planning when compared with actual walking times. Temporal differences between simulations of different routes can indicate regional hierarchies in a spatial environment and thus explain the successful modelling through hierarchical approaches ([McNamee, Wolpert and Lengyel, 2016](#)). Still, these findings only reflect planning behaviour on a higher level across potential regions to account for the compression effect found for entire routes. On the level of planning each step of the journey, evidence of hierarchical planning is still missing for an ecologically valid, real-world environment. In particular, response times between individual streets and their systematic variation with street network features could provide insight into the way the environment impacts route planning.

Real-world environment

Real-world cities often consist of a complex and large street network, such as London's street network with about 53,000 streets. In contrast to well-controlled environments in experimental setups that use confined spaces and artificially imposed, accentuated hierarchies (e.g. [Balaguer, Spiers, Hassabis & Summerfield, 2016](#); [Arnold, Iaria & Ekstrom, 2016](#); [Wiener & Mallot, 2009](#); [Wiener, Schnee & Mallot, 2004](#); [Schick, Halfmann, Hardiess, Hamm & Mallot, 2019](#)), real-world cities often lack an obvious segregation of city districts. Instead, districts perceptually often blend into each other without consciously perceivable boundaries (e.g. City of London and Farringdon). Still, in London there exist historically developed districts with structures that individuals agree on and consciously perceive as boundaries (see **Chapter 3**). These spatial structures consist of streets (e.g. Regent's Street) or geographical features (e.g. [Lynch, 1960](#)), such as parks (e.g. Hyde Park) and waterways (i.e. the River Thames). They separate areas (e.g. north versus south of the River Thames) or entirely surround districts, such as Shaftesbury Avenue, Regent's Street, Charing Cross Road and Oxford Street, which enclose the district of Soho. These districts with distinct boundaries that have been consistently identified by licensed London taxi drivers are Mayfair, Soho, Belgravia, Whitehall, Southbank, Regent's Park, Hyde Park, Battersea Park, the Congestion Charge Zone north of the River Thames and the River Thames (see **Section 3.4**).

Such a consciously perceived segregation of London through prominent districts could facilitate a hierarchical representation and hierarchical route planning analogously to the subway lines in the transportation network found by Balaguer and colleagues ([2016](#)). Here, instead of the number of stations to the destination, the number of contexts scaled with response times. Similarly, if humans were to plan routes across the London street network and recall each street analogously to the stops in the transport network, similar effects would be expected as found for the transportation network ([Balaguer, Spiers, Hassabis & Summerfield, 2016](#)). In particular, for the street network environment, the number of districts that are being crossed should scale with response times of route planning events instead of the number of streets to the destination. However, in contrast to the subway network, for London the boundaries as identified in **Chapter 3** are less obviously and clearly perceived as they underlie gradual agreement rates (from no agreement to entire agreement). Often there are parts of district boundaries with low agreement that result in districts that are not entirely perceived to be enclosed by

boundaries (e.g. Shaftesbury Avenue and Charing Cross Road reach lower agreement than other boundaries in Soho). A hierarchical segregation of the environment thus proves less obvious in this sense and could thus be impacted by the fragmentation of the boundary perception. Instead, the actual boundaries and their agreement rates could be better analysed in line with previous findings. In particular, Balaguer and colleagues (2016) also found an effect of (a) the type of station when comparing exchange stops with regular stops, (b) switches between different lines and (c) the cost of U-turns (cf. **Figure 4.2**). Therefore, analogously, it would be expected that an impact of (a) boundary streets when compared with non-boundary streets, (b) switches between areas separated by boundary streets and (c) travelling away from the goal will impact response times of route planning in a street network.

Apart from the potential impact of boundaries as found in the transport network, the street network allows for additional features that can impact on route planning. These include turns (e.g. [Brunec, Ozubko, Ander, Guo, Moscovitch & Barense, 2020](#)) and Euclidean or path distance (e.g. [Bonasia, Blommestejn & Moscovitch, 2015](#)), as well as potential road classifications into main and minor roads ([Pailhous, 1969](#)). These studies suggest turns and road types to impact the planning of routes over distances. In this context, turns have been found to act as conceptual boundaries that impacted on memory recall of route features ([Brunec, Ozubko, Ander, Guo, Moscovitch & Barense, 2020](#); [Lloyd, 2013](#); [Kuipers, Tecuci & Stankiewicz, 2003](#)), the estimation of path distances ([Hutchenson & Wedell, 2009](#); [Sadalla & Staplin, 1980](#)) as well as preferences towards routes with fewer turns ([Venigalla, Zhou, Zhu, 2017](#); [Broach, Dill, Gliebe, 2012](#); [Elliot & Lestk, 1982](#)). Analogously, a potential better mental representation of major roads due to more familiarity, as with Parisian taxi drivers ([Pailhous, 1969](#)), would favour a faster recall of those over minor roads. Therefore, during the route recall of a mentally planned route, major roads and non-turn sequences of roads should be recalled faster than turns actions or travelling minor roads.

Whilst there is evidence of mental compression for distance estimates ([McNamee, Wolpert and Lengyel, 2016](#); [Bonasia, Blommestejn & Moscovitch, 2015](#)), greater distances are often associated with more streets and planning actions that have to be solved (e.g. [Huys, Eshel, Onions, Sheridan, Dayan & Roiser, 2012](#); [Milford & Wyeth, 2007](#)). In a non-hierarchical representation of space, longer distances and routes with more streets would scale with a higher cognitive load and, thus, longer response times at each step. In a hierarchical representation, that reduces the cognitive load of the route

planning to shorter sequences as particular plans are carried out on a local level (i.e. within specific districts or modules), distance effects for Euclidean or path distances play a little role in determining the plan throughout the planning responses.

4.3. Methods

This study was seeking to find evidence of hierarchical route planning in a real-world environment and identify spatial features and properties that facilitate such a hierarchical planning behaviour. Key to testing these is a near immaculate familiarity with the London street network and an ability to naturally give precise travelling instructions that could be recorded and traced geographically. Such knowledge of London would allow for a comparison of route planning across all participants. However, prevalent in the general population of London are individual differences in familiarity with the street network owed to different individual experiences and often locally limited to neighbourhoods. However, in contrast to the general population, licensed London taxi drivers (with a green badge) are trained to recall routes in all areas of London by giving precise, legal travelling instructions (i.e. forward and turn activities at given streets) and specific street names. Additionally, years of driving experience in London, accumulated during training, as well as post-qualification during work, make taxi drivers natural navigators of London, who fit the requirements of this study.

Data was collected in two periods with an interval of six months between the collection times as part of undergraduate and postgraduate projects and approved by the ethics committee (CPB/2013/150 and EP/2018/008). The first set of data was collected by Emily Hoy, Layla Massoud, Florence Stow, Agnese Merlo, Lea Evers, and the second set of data by Ishita Aradhey, Ola Volhin, Dalton Barham and Elahi Hossain.

Participants

49 taxi drivers agreed to take part in this study. Five taxi drivers decided to withdraw at an early stage. In addition, one driver displayed extremely unstructured route recalls that did not allow for a transcription of the routes. The data of these six taxi drivers was removed from the data set. In total, data from N=43 taxi drivers (41 males, 2 females) was analysed. Their mean age was 53.82 years ($SD = 10.35$; range: 34-75 years) and their mean experience driving a taxi amounted to 19.61 years ($SD = 15.69$). 19 taxi drivers (all male, age = 52.94, $SD = 9.81$, experience = 19.97, $SD = 16.52$) participated in the first

round of data collection and 24 taxi drivers (22 male, 2 female, age = 54.50, SD = 10.93, experience = 19.30, SD = 15.32) at the second round of data collection, recruited either from the taxi rest rank at Russell Square, or a taxi café near King's Cross station in the borough of Camden, London (UK). All of the taxi drivers were native speakers and new to the study at each period of data collection.

Material

The tasks for the first data collection consisted of 12 origin destination pairs (**Table 4.1**, Study 1). For the second data collection, only two origin-destination pairs of the original set remained the same to allow for a comparison across the two groups of participants and task properties (i.e. different travel direction and task complexity). The rest of the route planning tasks was replaced through novel origins and destinations to allow for a greater variety of route planning problems across London (**Table 4.1**, Study 2). From the two tasks that remained the same, one origin location had to be updated (from Joe Allen's restaurant to Bill's) because the restaurant had moved location. The new origin (Bill's) was a neighbouring restaurant to the original (Joe Allen's restaurant). All tasks were designed to vary in their geographical properties (e.g. path length, Euclidean distance, direction of travel; see **Table 4.1** and **Supplementary Figure 8.1**). For instance, distance was relatively decorrelated from the number of streets to the goal and potential boundaries that had to be crossed. For instance, task 7 and 18 had a similar number of streets (expected were 8 streets for task 7 and 7 streets for task 18), but varied in their planning distance (about 11km for task 7 and 1.5km for task 18; **Table 4.1**). On the other hand, task 7 and task 17 were similar in their planning distance (about 11km vs 8.4km), but varied in the number of streets that had to be recalled (8 streets vs 14 streets). Similarly, the number of boundaries that expected to affect routes varied across tasks: Some tasks did not cross any boundaries (e.g. task 4, 6 or 10), other tasks required at least partially to mentally travel along boundaries (e.g. task 7, 12 or 14) or crossing several boundaries (e.g. tasks 1, 5, 13, 16 or 17). In collaboration with a knowledge school, teachers provided feedback to ensure the validity of the selected task with regards to route planning properties.

Two SONY ICD-PX240 Mono Digital Voice Recorders were used in this experiment. One of the recorders was used to replay pre-recorded instructions and the route planning

tasks. With the second recorder, the experimenters record the whole duration of the experiment, from the initial task presentation to the final route recall.

Table 4.1. Geographical Properties of Study Tasks.

Study	No	Start Location	Goal Location	Distance (km)			Cardinal Direction ¹
				Euclidean	Shortest Path	Google	
1	1	Chelsea Harbour <i>Chelsea Harbour Drive</i>	London Heliport <i>Bridges Court</i>	0.853	2.863	3.7	161
1	2	The Radisson Edwardian Sussex Hotel <i>Granville Place</i>	The Grange Fitzrovia Hotel <i>Bolsover Street</i>	1.269	1.813	1.9	47
1	3	Putney Bridge Station <i>Ranelagh Gardens</i>	Harrods <i>Brompton Road</i>	4.669	5.610	5.4	42
1	4	The Kuwait Health Office <i>Devonshire Street</i>	Selfridges <i>Orchard Street</i>	0.984	1.318	1.4	208
1	5	The Tate Modern <i>Holland Street</i>	Moorgate Station <i>Moorgate</i>	1.518	2.602	3.6	36
1	6	Marlborough London Arts Gallery <i>Albemarle Street</i>	Buck's Club <i>Clifford Street</i>	0.270	0.596	0.600	358
1	7	Savoy Circus <i>Westway</i>	Old Street Station <i>Old Street</i>	11.172	12.272	11.9	83
1	8	Joe Allen's Restaurant <i>Exeter Street</i>	The Doubletree Courthouse Hotel <i>Great Marlborough Street</i>	1.375	2.087	1.9	282
1	9	Stockwell Station <i>Clapham Road</i>	The Royal Hospital in Chelsea <i>Royal Hospital Road</i>	3.024	4.539	4.7	306
1	10	The Savoy Hotel, River Entrance <i>Savoy Place</i>	The Royal Society of Arts <i>John Adam Street</i>	0.242	1.409	0.550	260
1	11 ²	Cutty Sark <i>King William Walk</i>	Island Gardens Station <i>Manchester Road</i>	0.626	7.698	7.8	353
1	12	The Home Office <i>Marsham street</i>	Monument Station <i>King William Street</i>	3.367	4.159	4.5	61
2	8 ³	Bill's <i>Exeter Street</i>	Double Tree Courthouse Hotel <i>Great Marlborough Street</i>	1.375	2.087	1.9	282
2	13	Royal Oak <i>Lord Hills Bridge</i>	Revolution <i>Clapham High street</i>	7.248	9.490	10.4	149
2	14	Zizzi St Giles <i>Bucknall street</i>	The Gate Theatre <i>Pembridge Road</i>	4.909	5.399	5.1	261
2	15	Maudsley Hospital <i>Denmark Hill</i>	Shoreditch Park <i>Mintern Street</i>	7.075	8.291	8.8	4
2	7	Savoy Circus <i>Westway</i>	Old Street Station <i>Old Street</i>	11.172	12.272	11.9	83
2	16	Elephant and Castle Stn <i>Elephant Rd</i>	Swiss Cottage <i>Finchley Road</i>	7.377	8.959	12.2	316
2	17	Tower of London <i>Tower Hill</i>	Holland Park Car Park	8.399	9.063	9.9	264
2	18	Euston Station <i>Exit on Eversholt Street</i>	Holborn Station <i>Holborn</i>	1.436	1.450	1.5	146

¹Direction of the goal location from origin; N = 0°; E = 90°; S = 180°; W = 270°

²Removed from data analysis due to invalid recall format

³Change of name

Procedure

Licensed London taxi drivers were recruited in the area of Bloomsbury and the borough of Camden, London (UK). Before participating in the study, taxi drivers gave written consent (ethics number: CPB/2013/150 and EP/2018/008) and filled in a personal questionnaire to indicate age, gender, experience and if they were native speakers or had taken part in this study on a previous occasion. After participating, taxi drivers received monetary compensation.

The first group of taxi drivers, who participated in the first study, were verbally informed that they were to plan routes (i.e. ‘runs’) between origin-destination pairs (i.e. ‘points’) and that these tasks would be presented through audio recordings. To force taxi drivers to listen carefully and avoid interferences with their initial route planning behaviour, drivers were asked to listen carefully to the instructions, and they were warned that repeating instructions was not possible. If they did not understand or know either of the points, they could skip the task or carry it out where they perceived the points to be. Moreover, drivers were instructed to disregard possible congestion and any temporary obstructions in the street network to avoid additional interfering effects from obstructions unrelated to street network properties. By instructions, they were also prompted to imagine they were carrying out the route planning tasks on a typical Monday morning

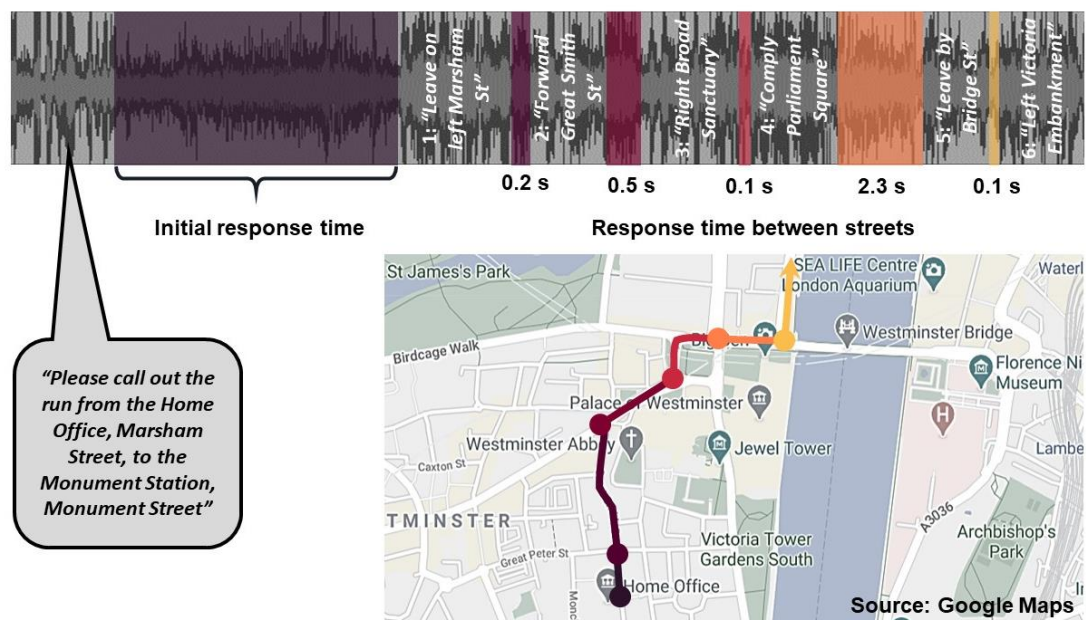


Figure 4.3. Route recall process. Taxi drivers received pre-recorded audio instructions of the origin and destination location and planned the route before being presented with the next task. All instructions and route recalls were audio recorded (top) and transcribed to extract response times and visualise planned routes (bottom right). The time lapse between given instructions and the first recalled street was defined as the *initial response time*. Time lapses between recalled streets of the route were defined as *response times between streets*.

around 11.00 AM to keep conditions consistent as in some traffic rules can change in dependence of day and time. Finally, taxi drivers were instructed to focus on the route planning as if they were in a knowledge examination situation and refrain from questions, comments or explanations to avoid distractions from the planning process and provide a structured recall across all drivers.

Instructions to follow the structured recall as in the examination situation were given only before the first and the second task, but drivers received a reminder of day and time (i.e. Monday morning at 11.00 AM) before each task. These reminders had been audio recorded and were presented together with the audio recordings of the twelve route planning tasks (**Table 4.1**) in the following format:

“Please remember to do this under appearance conditions. So, no questions or clarifications, when you hear the points. If you’re unsure, start or go where you think it is, or skip the run.” (Before task 1 and 2)

“Please remember, you’re doing the next run on a Monday morning around 11 am.” (Before each task)

“Please call out the run from [Point, Street] to [Point, Street].” (Task presentation)

Drivers listened to the set of instructions and then planned the route before moving on to the next set of instructions and route planning task. An illustrative example of a recall block can be found in **Figure 4.3**. The whole sequence from the first instruction to the final route recall was audio-recorded on a second audio recording device.

The second group of taxi drivers, who were presented with a modified set of eight origin-destination pairs (**Table 4.1**), the following additional modifications were put in place to improve the procedure and avoid uncertainty that previously impacted the planning behaviour:

During the first period of data collection, several taxi drivers repeatedly asked for clarifications of the origins or destinations or could not remember which location was named. Thus, several tasks were skipped by drivers. Therefore, flashcards were provided stating the location and the corresponding street for both origin and destination. These flash cards were shown to the drivers directly after they had listened to the audio recorded task and stayed visible during the entire route recall of a task. Additionally, after completing the first and second task, drivers were asked for confirmation that the recalled

route would reflect what they would have done on a Monday morning at 11.00 am, which all taxi drivers confirmed.

Analysis

The collected verbal data of the recorded route recalls was transcribed with regards to street names and response times. Response times were calculated as the time lapses between task instructions and the first street named (i.e. ‘*initial planning times*’) or as pauses between two consecutively named streets (‘*response times between streets*’, see **Figure 4.3**).

The transcription of all response times was carried out with the free and open source audio software Audacity, versions 2.2.2 and 2.3.1 ([Audacity, 2020](#)), which allowed for an accuracy of up to 0.1s. The street names were transcribed and corrected for mistakes (e.g. “Townsend Rd” to “Townmead Rd”) or unified (e.g. “Charles the 1st” to “Trafalgar Square”) to ensure comparability of response times at each street or place. The analysis of the complete dataset was carried out in R (version 4.0.2).

To ensure the reliability of transcribed response times across experimenters, an inter-rater reliability (IRR) test was carried out for both studies. The intraclass correlation coefficient (ICC) for the first study (transcribed by two experimenters), was assessed through a two-way, mixed effects, absolute agreement, single-measures model. The ICC (ICC = 0.98, $p < .001$) was in the excellent range, suggesting a similar transcription of response times due to a high agreement between the two raters. For the second study (transcribed by four raters), a one-way random effects model with absolute agreement was used. Across the four raters, the ICCs indicated a moderate range of agreement (ICC = 0.61, $p < .001$), which was considered good enough across multiple raters.

The data from both times of data collection was treated as one data set as a Wilcoxon Signed-rank test indicated no group differences between the two sets of taxi drivers for tasks 7 and 8 for log-transformed (Mdn(S1) = -0.22, IQR = 1.18, Mdn(S2) = -0.16, IQR = 1.24, $p = .252$, $r = .046$) or z-standardised (Mdn(S1) = -0.29, IQR = 1.11, Mdn(S2) = -0.33, IQR = 1.24, $p = .688$, $r = .016$) response times between streets.

4.4. Results

This study focused on the route planning behaviour of humans in a real-world environment. Specifically, the study tested if a hierarchy, imposed by spatial features such as district boundaries, was underlying the route planning behaviour of individuals who are highly familiar with the entire street network of London, such as licensed London taxi drivers. To test this, licensed London taxi drivers were asked to plan and recall routes between origin-destination pairs located in London, a task that taxi drivers are trained to carry out as part of their qualification.

Response times were classified either as *initial response times* (i.e. time lapses between instruction and the beginning of the route recall) or *response times between streets* (i.e. time lapses between two consecutively recalled streets without pronunciation of street names, cf. **Figure 4.3**). However, initial response times reflected route planning behaviour that would include a variety of actions and processes inconsistent across drivers or tasks. Some of these actions were not related to active route planning (e.g. affirmative questions concerning locations), whilst other actions included amongst other the visualisation of places, consideration of alternatives, unspecific planning on a higher level or precise planning on a lower level. These actions were reported by drivers as not used consistently across or within taxi drivers, or tasks, and could not be separated from each other analytically, because most planning was carried out silently (except for occasional verbalisation of thoughts) to ensure natural planning behaviour of the drivers. Therefore, initial planning times have been excluded from the analysis in this study, except for initial, descriptive analysis. In contrast to initial response times, response times between streets were part of the sequential recall of street names and reflected planning behaviour directly related to each point of the recall process, not leaving opportunities for unrelated or diverse planning actions.

STUDY 1 (N=19)



1. Chelsea Harbour to London Heliport; Recalls: 18



2. The Radisson Edwardian Sussex Hotel to The Grange Fitzrovia Hotel; Recalls: 10



3. Putney Bridge Station to Harrods; Recalls: 18



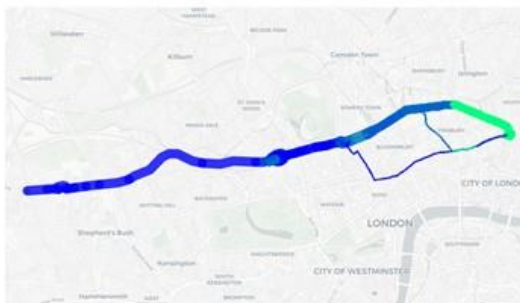
4. The Kuwait Health Office to Selfridges; Recalls: 16



5. The Tate Modern to Moorgate Station; Recalls: 18



6. Marlborough Arts Gallery to Buck's Club; Recalls: 6



7. Savoy Circus to Old Street Station; Recalls: 16 (recalls across both studies: 40/43)



8. Joe Allen's Restaurant to The Doubletree Courthouse Hotel; Recalls: 18 (recalls across both studies: 41/43)



9. Stockwell Station to The Royal Hospital in Chelsea; Recalls: 17



10. The Savoy Hotel to The Royal Society of Arts; Recalls: 16



12. The Home Office to Monument Station; Recalls: 18

STUDY 1 (N=24)



7. Savoy Circus to Old Street Station; Recalls: 24 (recalls across both studies: 40/43)



8. Joe Allen's Restaurant to The Doubletree Courthouse Hotel; Recalls: 23 (recalls across both studies: 41/43)



13. Royal Oak to Revolution; Recalls: 24



14. Zizzi St Giles to The Gate Theatre; Recalls: 18



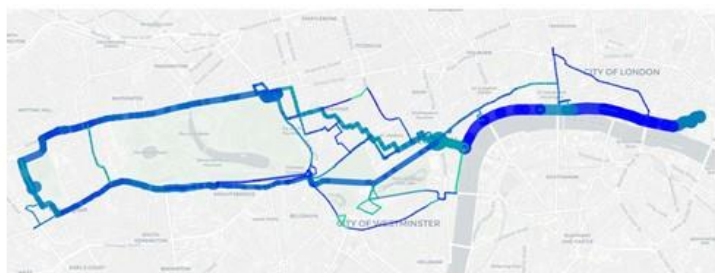
16. Elephant and Castle Station to Swiss Cottage; Recalls: 24



18. Euston Station to Holborn Station; Recalls: 23



15. Maudsley Hospital to Shoreditch Park; Recalls: 21



17. Tower of London to Holland Park Car Park; Recalls: 24

Figure 4.4. Mapped route recall. The recalled routes from Study 1 and Study 2 were mapped in an overlay and colour coded to reflect the speed of standardised (z-transformed) response times between streets (blue: fast recall, green: slow recall). Captions of the mapped routes contain origin and destination location as well as the corresponding number of taxi drivers who provided a route recall for the task. For tasks 7 and 8, which were tested in both studies, the total number of taxi drivers across both studies is additionally provided. Source: Adapted from data mapping by Prof Ed Manley, University of Leeds.

Initial Overview of the Dataset

The data, which was collected from $N = 43$ licensed London taxi drivers (green badge holders), included the recall of 354 routes (first study: 173, second study: 181). The mean for *initial planning times* was $M = 13.83s$ ($SD = 13.40$, cf. **Table 4.2**) over $N = 315$ routes. Data of some initial planning events had to be removed as drivers asked for clarifications and tried to engage in conversations. On average, taxi drivers recalled 9.1 routes out of 12 during the first and 7.5 routes out of eight during the second study. For each task, these recalled routes were visualised in an overlaid mapping (**Figure 4.4**), also highlighting the recall speed of slow (green) and fast (blue) responses with which streets have been recalled. Taxi drivers' agreement on chosen routes varied across tasks. For straight routes (tasks 7 and 18) and routes with few potentials for alternative routes (e.g. tasks 1 and 10) taxi drivers overlap more in their route choice than for tasks that offer a number of alternative options (e.g. tasks 13 and 16).

The number of response times between streets amounted to a total of 3398 responses with a mean *response time between streets* of $M = 1.82s$ ($SD = 3.24$, cf. **Table 4.2**). The *total response duration* for tasks, a measure to reflect the total planning duration based on responses between streets per driver and route, was $M = 17.53s$ ($SD = 16.47$, cf. **Table 4.2**). For the raw dataset, these response times between streets were skewed towards minimal response times (**Figure 4.5**). Log-transformation (using the natural logarithm, \log_e) and z-standardisation provided a better fit with a normal distribution with exception of high density at minimal response times of the log-transformed data (**Figure 4.5b, c**). This was also reflected on task level (**Supplementary Figure 8.2**). Here, mean response

Table 4.2. Variable Summary for recalled data

	N ¹	Mean	SD	Min	Max
Initial Planning Time² (sec)	315	13.83	13.40	1.00	102.00
Mean Response Times between Streets² (sec)	3398	1.82	3.24	0.10	61.4
Total Response Duration^{2,3} (sec)	354	17.53	16.47	0.20	89.40
Total no of Streets Recalled	354	10.71	5.71	3.00	30.00
Standard Deviation per Recalled Route²	354	2.18	2.05	0	16.55

¹Number of occurrences in data set

²minimum coding accuracy of response times: 0.1s

³mean of the sum across all response times between Streets per taxi driver and per planned route

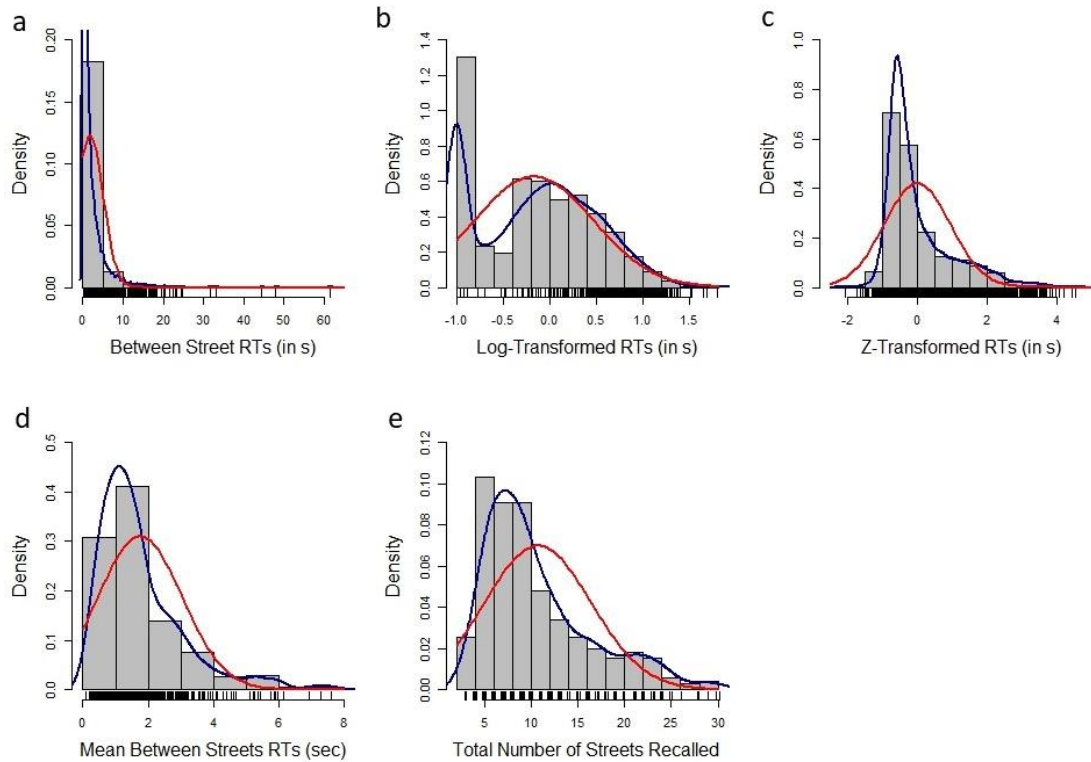


Figure 4.5. Summary of response time distributions. Distributions of initial response times for the raw (a), the log-transformed (b) and the z-standardized (c) data, as well as the mean of the response times between streets per task and driver (d) were plotted. Figure (e) visualises the total number of streets that were recalled. Fitted distribution (blue line) and normal distribution (red line) indicate skewness of the raw data (a) and a best fit for log-transformed RTs (b) over z-standardised RTs (c). The fitted distribution (blue line) of raw between street RTs was cut off as it exceeded the plot beyond y-scale limits. Note: The cut off point for transcription of fast response times between streets was at 0.1 sec (fastest RTs).

times between streets ranged from 0.7s for task 10 to 2.8s for task 9 (**Figure 4.6a**) and violin plots indicated skewness of raw data towards fast recalls between streets (**Figure 4.6b**). These were ordered by ascending means of z-transformed data to allow for comparison across tasks whilst accounting for individual differences between drivers (**Figure 4.6d**). A high number of outliers for the raw and z-transformed data at each task highlighted slow responses between named streets with up to 60s (**Figure 4.6b**, task 8). Log-transformed violin plots (**Figure 4.6c**) showed two high density peaks of data, one near very fast recalls around 0.1 s (log-values around -1) and a second density peak near values of 1s (i.e. log-values around 0). For this study, the high density of fast recalls (around 0.1s) was thus considered as a measurable lower bound on response times. In contrast, deviations towards slower responses (i.e. second density peak of log-transformed data and outliers in the raw and z-transformed data set) were expected to carry information about spatial structures indicative of potential planning of new sequences and thus hierarchical planning.

Similar to response times between streets, the means of response times between streets by task (**Figure 4.5d**), the total number of recalled streets per task (**Figure 4.5e**) as well as initial response times were left-skewed for raw data. After log-transformation and z-standardisation initial response times fit a normal distribution (**Supplementary Figure 8.3a-c**). No relation was found between raw or transformed initial response times and mean response times between streets (**Supplementary Figure 8.3d-f**). Thus, there was no evidence that initial planning impacted how fast a route was later described street-by-street.

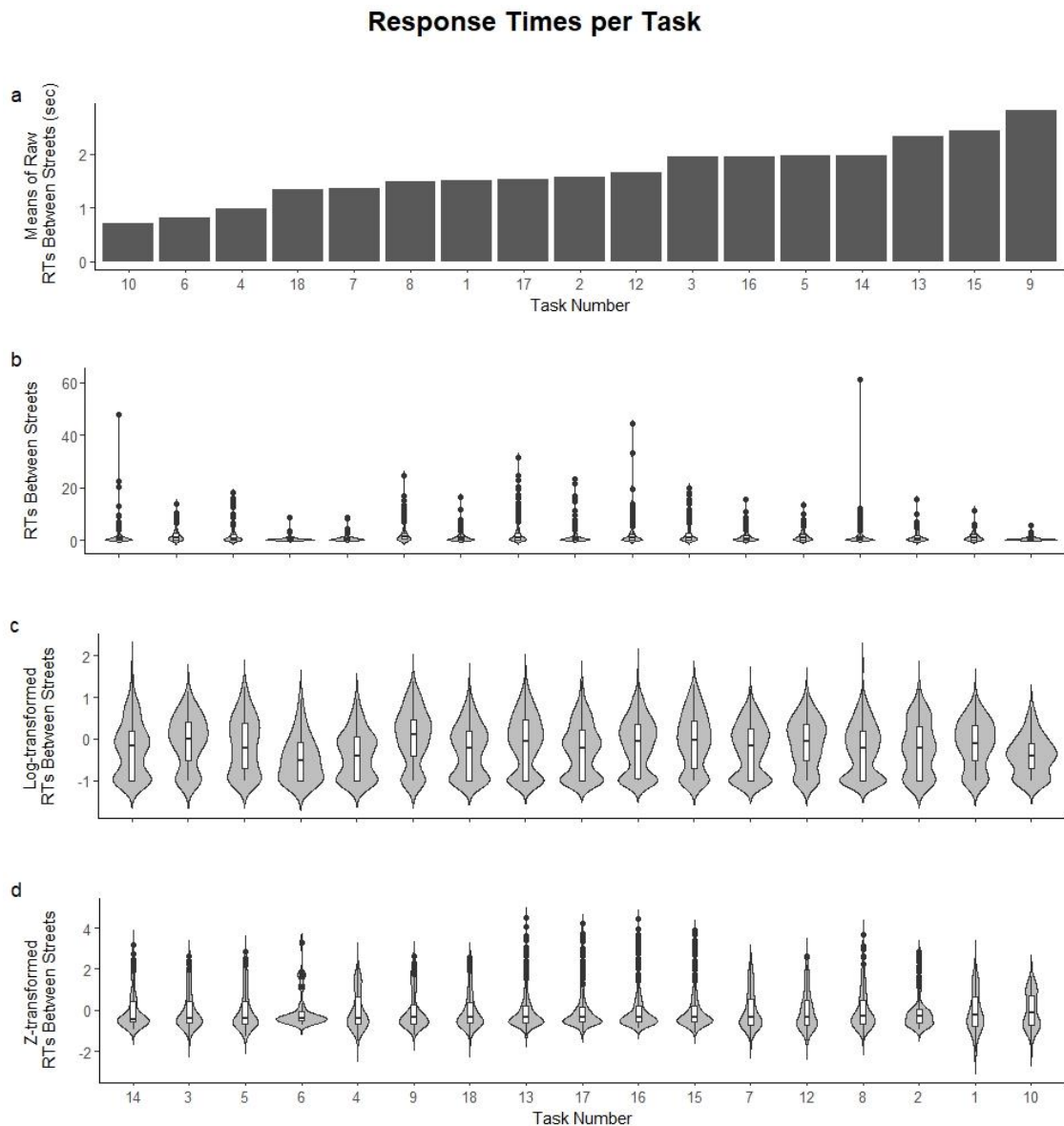


Figure 4.6. Response times for each task. (a) Bar plot of the mean response times between streets for each route by speed in ascending ordered (0.7s for task 10 to 2.8s for task 9). Violin plots of the raw (b) and z-transformed (d) RTs between streets indicate a range of response times outside the interquartile range for all runs. Violin plots of the log-transformed data (c) highlight the density distribution of data for each run. Cf. **Figure 4.4**

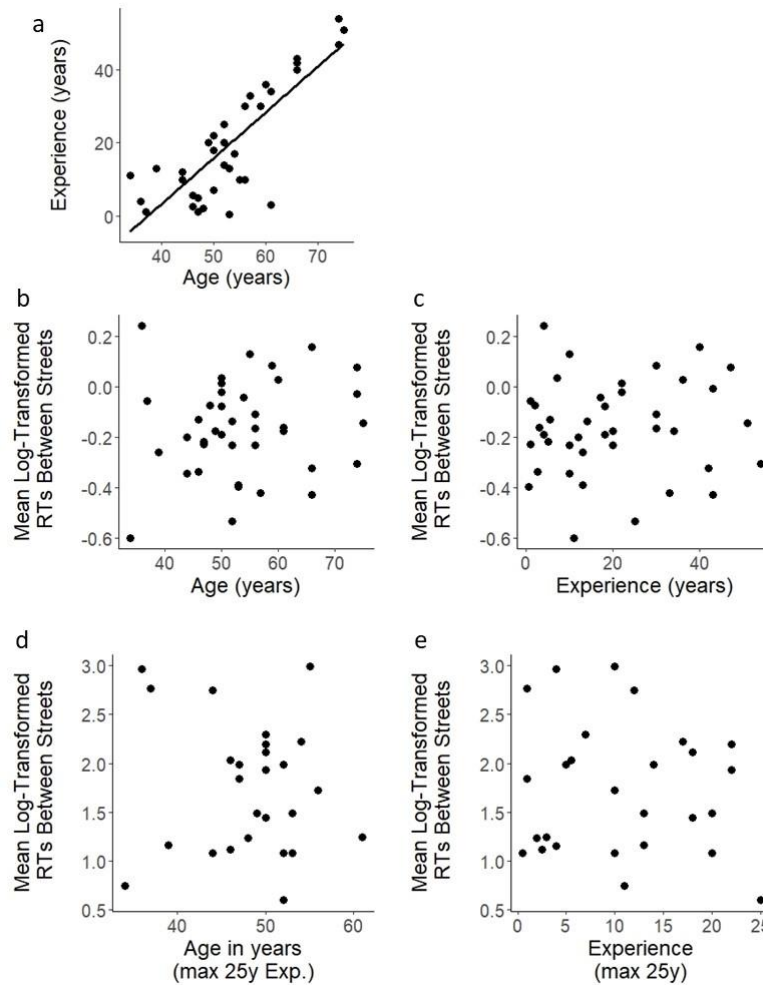
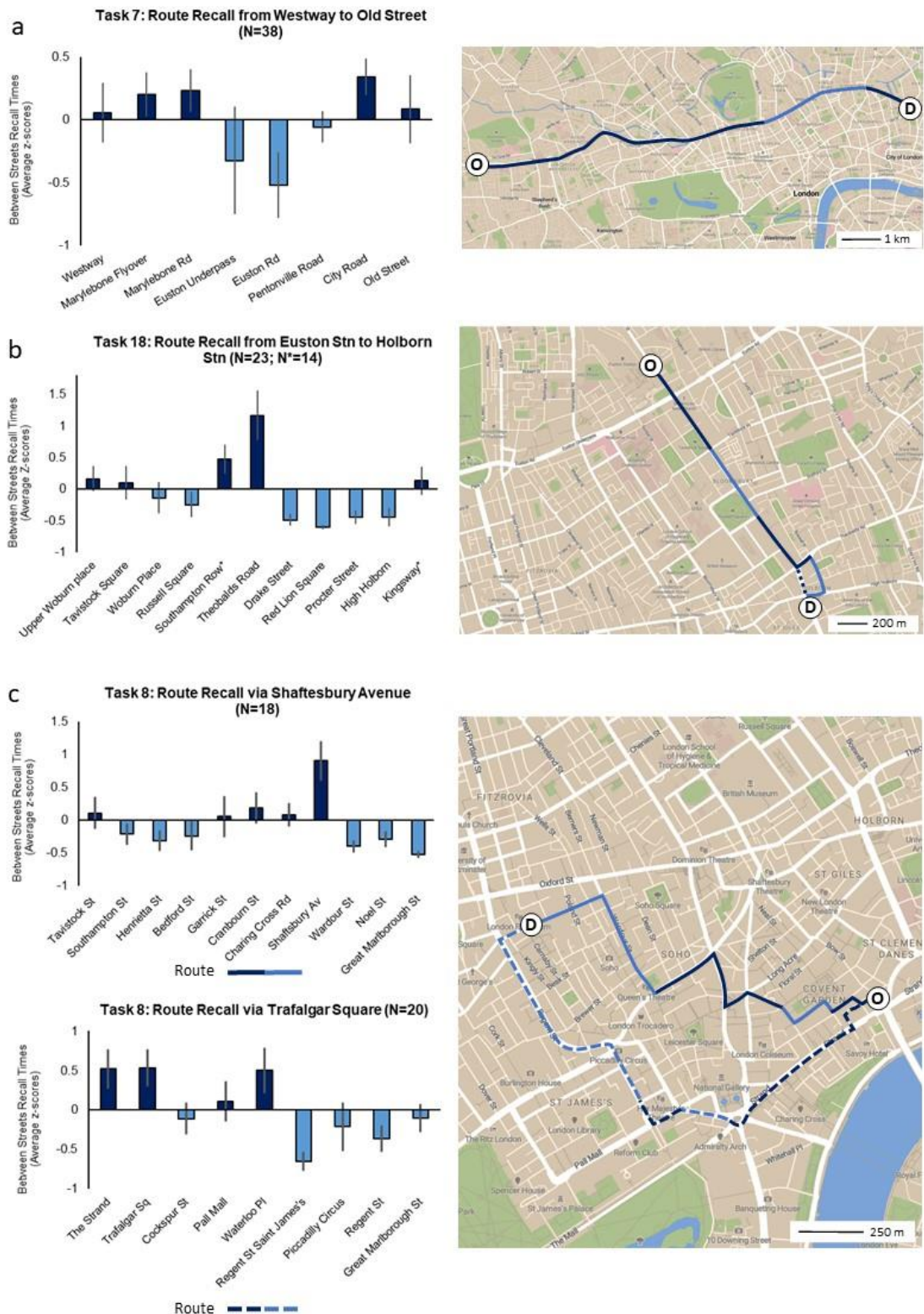


Figure 4.7. Age-experience relationship. Age and experience across taxi drivers was strongly correlated for the entire group of participants (a), but decorrelated for a subset of drives with 25 years of experience or less. Neither the entire group of taxi drivers (b, c) nor the subset of drivers with 25 years of experience or less showed any relation to mean log-transformed response times between streets.

Age and Experience

For the group of 43 taxi drivers the relationship between age ($M = 53.82$ years, $SD = 10.35$) and experience driving a taxi ($M = 19.61$ years, $SD = 15.69$) was studied. For this group of taxi drivers, a Spearman correlation indicated a strong, significant positive relation of age and experience ($r_s(43) = .73, p < .001$; see **Figure 4.7a**). For a group of taxi drivers with 25 years of experience or less, age and experience were decorrelated ($r(24) = .23, p = .564$). No relation was found between means of log-transformed response times by task and experience ($r_s(40) = .08, p = .623$; **Figure 4.7b**) or age ($r(37) = .13, p = .445$; **Figure 4.7c**) for the entire group of taxi drivers. There was also no relation for the decorrelated group of taxi drivers with 25 years of experience or less (experience: $r(25) = -.11, p = .584$; age: $r(24) = -.11, p = .603$; **Figure 4.7d & e**).



Route Recall

To test the impact of boundaries and spatial features of the street network (i.e. Euclidean distance and road type) on route planning behaviour, response times between streets were analysed (see **Figure 4.3**) in association with these street network structures. An initial impression of how response times vary in relation to streets was gained from the response times related to a set of routes with high overlap across taxi drivers. **Figure 4.8** highlights three tasks (task 7, 18 and 8), for which a high number of taxi drivers agreed on one specific route or two alternative routes had high agreement (task 7: $N = 38$; task 18: $N = 23$; task 8: $N = 18$ and $N = 20$; further examples can be found in **Supplementary Figure 8.4**). To account for individual differences in response speed across drivers, the means across all z-standardised response times was used. Across routes, mean z-standardised response times above route means (i.e. > 0) were highlighted in dark blue and those below route means (i.e. < 0) in light blue. For straight routes (**Figure 4.8a, b**; **Supplementary Figure 8.4a, b**), as well as routes with turns (**Figure 4.8c**) or bifurcations (**Supplementary Figure 8.4c**) sequential modulations of faster and slower recalls along the route were found. For a straight route with no turns the modulations of responses were smaller (e.g. between $-0.52s$ and $0.34s$ for task 7, **Figure 4.8a**) than for other routes. Extreme values were found for a point of divergence (i.e. Theobald's Rd, **Figure 4.8b**) and an intersection of major roads at the boundaries of Soho (i.e. Shaftesbury Ave, **Figure 4.8c**). At the point of divergence, a number of drivers planned a turn into Theobald's Road ($N = 9$) instead of going straight ($N = 14$). The mean z-standardised recall times of the final sequence of streets was recalled faster for several tasks (see **Figure 4.8b, c**; **Supplementary Figure 8.4b, c**).

To test effects of variables from the street network on the log-transformed response times from the recall of routes, a linear mixed effects model was used (c.f. [Coughlan, Coutrot, Khondoker, Minihane, Spiers & Hornberger, 2018](#)). Taxi drivers and their routes were entered as random effects to account for individual differences and potential correlations between repeated measures. The fixed effects variables of the model were *boundaries (B)*, *turn actions (T)*, *number of streets (N)*, *road type (R)* and *Euclidean distance (E)*. Here, the *boundaries* reflected agreement rates across taxi drivers in percentages. In a previous study (see **Chapter 3**) taxi drivers indicated on a map which streets they perceived as boundaries of districts. These agreement rates were entered in this study. The *number of turns* was extracted from the route recall. Turns were coded

categorically as ‘turn’ where a change in direction occurred between consecutive streets (e.g. Charing Cross Road, left into Shaftesbury Avenue, **Figure 4.8c**) or as a ‘forward’ action where streets continued straight without a change of direction (e.g. Euston Road, forward Pentonville Road, **Figure 4.8a**). The *number of streets* to the destination was counted down, with the last street having the value 1 (e.g. Old Street: 1, **Figure 4.8a**) and the first street the value n (e.g. Westway: 8; **Figure 4.8a**), if a driver recalled n numbers of streets for a route. *Road type* was categorised as either a main road or other roads to test if previous findings with Parisian taxi drivers could be replicated ([Pailhous, 1969](#)). Roads classified as main roads were either trunk roads or primary roads, all remaining road types (i.e. secondary, tertiary, residential roads) were classified as other roads. Here, data about road type classifications was extracted from the OS MasterMap Integrated Transport Network (ITN) Layer ([2018](#)). *Euclidean distance* to the destination was calculated from each intersection of two consecutive streets to the destination (see **Supplementary Figure 8.5**). Data was extracted from OS MasterMap Integrated Transport Network (ITN) Layer ([2018](#)). These five fixed effects were decorrelated as all variance inflation factors were below 2.5.

The basic model, which was used to describe log-transformed response times between streets, had the following structure:

$$\text{Log(RTs)} \sim 1 + \text{B} + \text{T} + \text{N} + \text{R} + \text{E} + (1 | \text{Taxi Driver}) + (1 | \text{Route}) \quad \text{Model 1}$$

This model revealed significant effects of *boundaries* ($b = -0.082, p < .05, 95\% \text{ CI} = -0.047 - -0.12$), *turns* ($b = 0.13, p < .001, 95\% \text{ CI} = 0.17 - 0.093$), *number of streets* to the destination ($b = 0.011, p < .05, 95\% \text{ CI} = 0.040 - -0.018$), and *main roads* ($b = 0.089, p < .05, 95\% \text{ CI} = 0.12 - 0.054$), but not *Euclidean distance* ($b = -0.038, p = .126, 95\% \text{ CI} = 0.013 - 0.063$). Coefficients of the model are also reported in **Figure 4.9a**. These parameters were additionally visualised individually in **Figure 4.9b-f**. The results indicate that turns and main roads were called out slower than non-turns (**Figure 4.9b**) and other roads (**Figure 4.9c**). The negative effect of boundaries indicated faster recalls for boundaries with higher agreement rates (**Figure 4.9d**). There was also a small, but consistent positive effect of the number of streets to the destination and slower response times when there are more streets to the goal (**Figure 4.9e**). This increase in response time speed, when comparing initial and final responses between streets, was not related to the total number of streets that had to be recalled (**Figure 4.9f**). Euclidean distance did

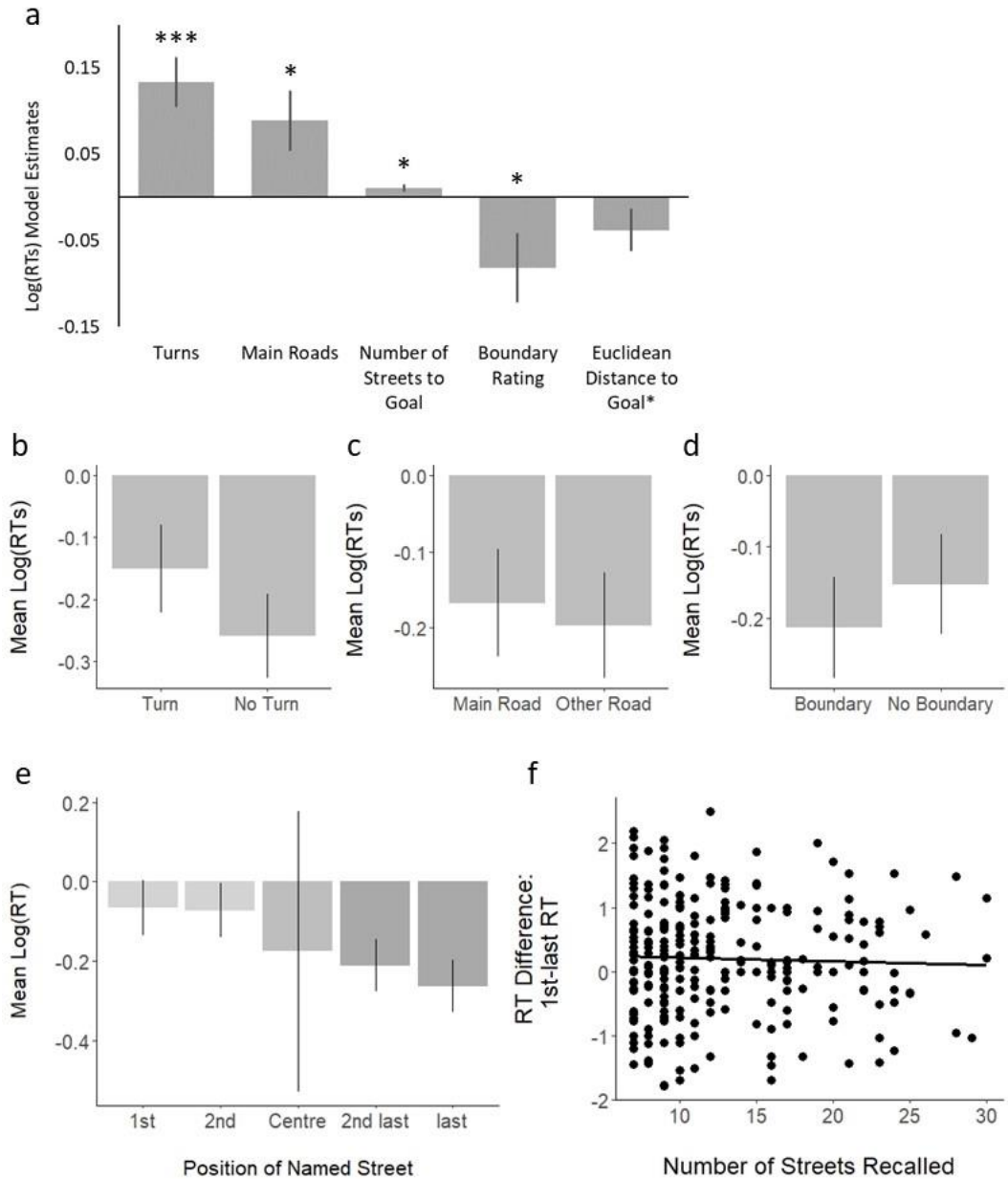


Figure 4.9. Model parameters. Model estimates (a) indicate a highly significant effect of turns. Main roads, the number of streets to the goal and boundary ratings with respect to agreement rates significantly impact on log-transformed response times. Euclidean distance does not reach significance level. Differences in the recall of turns and non-turns (b), main roads and minor roads (c) and boundary streets and non-boundary streets (d) show slower recall of turns and main roads and faster recalls of boundaries. Additionally, the position of the street along the sequential recall highlights differences between initial and final streets (e).

not contribute to the outcome of the model, i.e. goals that are far away did not lead to slowed responses compared to streets that were recalled closer to the goal.

Model 1 was designed to provide an initial assessment of the data based on factors found in literature. Since this model indicated an impact of boundaries, follow up analysis was carried out to examine in more detail the effect this model indicated and two alternative models were considered. The first model (**Model 2**) replaced boundary streets with the London district of *Soho* (*S*), including its boundaries, to test differences in log-

transformed response times between streets for an entire area that is perceptually different from its surrounding areas. Soho was chosen as it was the only district that conceptually appears as an ‘*island*’ with strong perceptual boundaries in the central London street network. In contrast, Mayfair and Belgravia are not entirely surrounded by other urban areas as they share boundaries with Hyde Park, a green space that is conceptually different from urban spaces. These areas are additionally lacking very high agreement at parts of their boundaries (see **Section 3.4**). The second alternative model (**Model 3**) examined the impact of circuitry, a similar concept to U-turn costs, instead of Euclidean distance. This analysis was carried out because Balaguer and colleagues (2016) found a cost of U-turns where participants had to head back along a line. Here, circuitry was defined as the fraction of path distance to the destination divided by Euclidean distance to the destination, both calculated from each street. The closer the circuitry value to 1, the more similar is the travelled route (path distance) to a straight line (Euclidean distance). Inversely, the larger the circuitry value, the more deviation there is of the path from a straight line (see also **Supplementary Figure 8.5**). Since circuitry and Euclidean distance to the goal were not independent from each other by definition, Euclidean distance was replaced by circuitry.

These alternative models considered here were:

$$\text{Log(RTs)} \sim 1 + S + T + N + R + E + (1| \text{Taxi Driver}) + (1| \text{Route}) \quad \text{Model 2}$$

$$\text{Log(RTs)} \sim 1 + B + T + N + R + C + (1| \text{Taxi Driver}) + (1| \text{Route}) \quad \text{Model 3}$$

The alternative **Model 2** revealed significant effects of *Soho* ($b = -0.16, p < .05, 95\% \text{ CI} = -0.094 - -0.23$), *turns* ($b = 0.14, p < .001, 95\% \text{ CI} = 0.17 - 0.11$) and *number of streets* to the destination ($b = 0.0095, p < .05, 95\% \text{ CI} = 0.014 - 0.0052$). The effect of *main roads* was marginally significant ($b = 0.089, p < .05, 95\% \text{ CI} = 0.95 - 0.029$) and *Euclidean distance* was again not significant ($b = -0.037, p = .135, 95\% \text{ CI} = -0.012 - -0.061$). Similar to the original model (**Model 1**) that contained boundaries, response times of streets recalled within Soho were faster than for the rest of the environment (see **Supplementary Figure 8.6a**). All other fixed effects variables indicated similar results, except or main roads, which only reach marginal significance.

The second alternative, **Model 3**, similar to the original model (**Model 1**), revealed a significant effect of *boundaries* ($b = -0.085, p < .05, 95\% \text{ CI} = -0.045 - -0.12$), *turns* ($b = 0.14, p < .001, 95\% \text{ CI} = 0.17 - 0.11$), *number of streets* to the destination ($b = 0.0061, p < .05, 95\% \text{ CI} = 0.0091 - 0.0032$), and *main roads* ($b = 0.084, p < .05, 95\% \text{ CI} = 0.12 -$

0.049). The effect of *circuity* was not significant ($b = 0.014$, $p = .272$, 95% CI= 0.026 - 0.001). Again, all fixed effects variables show similar effects, including *circuity*, which replaced Euclidean distance and did not have an effect either (**Supplementary Figure 8.6b**).

Points of Divergences

Since response times at decision points (see **Figure 4.8b**) additionally impacted route planning behaviour, descriptive analysis was carried out at such points. Here, decision points were defined as points, where two groups of taxi drivers consisting of at least three individuals each, agreed in their route plan on the same route before the two groups were diverging into different directions (see dashed boxes in bar charts and circles in maps of **Figure 4.10**).

In addition to the decision point in task 18 (**Figure 4.10d**), there were only three more points of divergence that met this criterion and allowed for a comparison of response times. These additional points of divergence (dashed boxes and circles), i.e. for the streets, where drivers diverged in their route plan for the first time, occurred at Kensington Highstreet (**Figure 4.10a**), after leaving Trafalgar Square (**Figure 4.10b**) and after leaving Parliament Square (**Figure 4.10c**). Increased response times were found at these decision points. Streets before divergence were recalled faster than average (**Figure 4.10a, b, c**), as were streets after divergence (**Figure 4.10a, b, d**). Means across all data indicates slower responses at the point of divergence when compared with streets before and after the divergence occurred (**Figure 4.10e**).

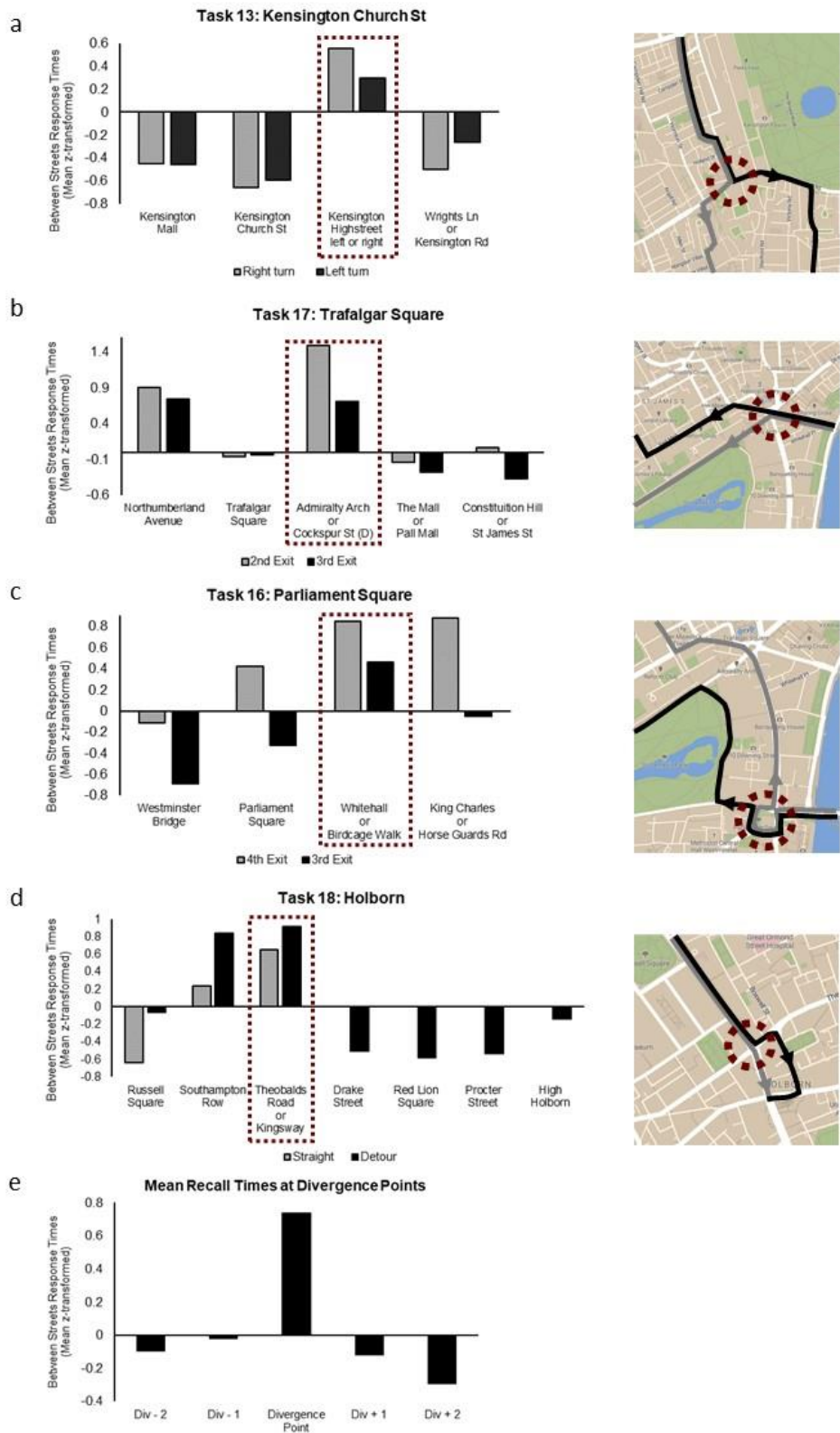


Figure 4.10. Divergence points. Z-standardised response times at points of divergence (dashed boxes), where taxi drivers choose between potential options (e.g. turning left vs right (a), exits at a roundabout (b, c), or turning left vs continuing straight (d)), are on average higher than response times before or after such divergence points. Combined data across all four points of divergence indicates a general tendency of higher response times at the point of divergence (e). Note: these figures only consist of data from few drivers. For Figure (d) no data was available after decision point for drivers choosing to go straight as Kingsway was the final destination. Map source: [Mapbox](https://www.mapbox.com/)

Linguistic Confounds

It could be argued that longer street names might take longer to articulate and recall the exact word, which might lead to longer response times between streets. To account for this potential linguistic confounds, log-transformed response times between streets were analysed in relation to the number of characters in a street name. There was no relationship between the two normally distributed variables (**Supplementary Figure 8.7**). A linear mixed model that additionally accounted for the number of characters as a fixed effect in the original model (**Model 1**) indicated no significant impact of the length of the street name ($b = 0.0033$, $p = .410$, 95% CI= $-0.00071 - 0.0074$). All other fixed effects variables were in line with previous model results (*boundaries*: $b = -0.082$, $p < .05$, 95% CI= $-0.12 - -0.042$; *turns*: $b = 0.13$, $p < .001$, 95% CI= $0.11 - 0.16$; *number of streets*: $b = 0.011$, $p < .05$, 95% CI= $0.0062 - 0.015$; *road type*: $b = 0.087$, $p < .05$, 95% CI= $0.052 - 0.12$; *Euclidean distance*: $b = -0.0384$, $p = .122$, 95% CI= $-0.063 - -0.014$). Thus, the length of the street names did not impact responses of the recall of individual streets (in log scale).

4.5. Discussion

The aim of this study was to test if route planning in a large, urban street network shows evidence of hierarchical structuring. In particular, the impact of perceived mental boundaries that segregate London into areas and districts was expected to give rise to a hierarchical mental representation in a real-world environment that would systematically impact the recall or routes. Therefore, licensed London taxi drivers were asked to verbally recall routes by street names and give precise travelling instructions for routes between origin-destination pairs in London. These verbal recalls allowed for a novel approach with an analysis of response times between individually named streets. This approach allowed to successfully link street-level responses to spatial information about the street network, the geography and in particular about previously collected data on mentally perceived boundaries of districts and areas in London (see **Chapter 3**). Results indicate a consistent pattern in modulations of response times in relation to spatial features, and specifically an impact of perceived hierarchical structures, such as district and area boundaries, as well as other spatial features during route planning.

Initial Findings

The verbal recordings of route recalls on 17 different routes that was collected from $N=43$ taxi drivers in London provided a data set consisting of 3,398 individual responses that were linked to street level information. The majority of these response times was extremely quick (0.1s) and on average it took taxi drivers 1.71s to recall a street, highlighting an incredible ability of spatial planning in a complex, urban environment among expert navigators. The spatial information that was linked to these responses included specific street properties that were found to impact route planning behaviour, such as road type, how streets connected through turns to other streets, where in the route sequence they occurred and the Euclidean distance to the destination. Of particular interest were mentally perceived boundaries of the street network that could account for a spatial segregation and facilitate hierarchical planning.

Evidence for hierarchical planning has been provided in a previous study by Balaguer and colleagues (2016) which explored planning in a virtual transportation network (**Figure 4.2**). Based on these findings, predictions for route planning in a real-world environment were adapted. In line with their study, street level variables were selected that were indicative of hierarchical planning (e.g. boundary streets). Since findings from Brunec and colleagues (2020) and Pailhous (1969) or Chase (1983) indicated an impact of turns and main roads on route planning and spatial representations, these variables were additionally included in the analysis of this study, as was Euclidean distance to the goal, a variable that is expected to scale with planning complexity as planning over more space would mean a more challenging plan to be carried out (e.g. [Huys, Eshel, Onions, Sheridan, Dayan & Roiser, 2012](#); [Milford & Wyeth, 2007](#)). Here, in a novel approach with ecologically valid, real-world data, these variables were combined in one model to explain response times of route planning events to test predictions in line with previous findings ([Balaguer, Spiers, Hassabis & Summerfield, 2016](#)), predicting an impact of boundary streets, distinct areas and detour costs (i.e. circuitry).

Mapping of the dataset (see **Figure 4.4**) highlighted the degree of consistency across drivers. Inspecting the data, it was apparent that taxi drivers agreed more on the same routes with tasks that allowed for linear routes with no turns (e.g. **Figure 4.4**, tasks 7 and 18). Routes involving multiple turns had the potential for alternative routes and were thus less consistent (see **Figure 4.4**, task 3 and 7). They showed a wider spread of routes in areas where no linear routes were available. Instead, origin-destination pairs diagonally

to the street network required consideration of options, such as where to turn or which bridge to choose (e.g. **Figure 4.4**, tasks 2, 4, 13 and 16). In this context, disagreement on route choices are likely to occur, especially where multiple alternative options with similar features are available (e.g. number of turns and deviations, see **Figure 4.4**, tasks 2 and 4). However, this does not account for a wide range of route choices across drivers that involved huge deviations from the direct line (e.g. crossing Lambeth Bridge or London Bridge on the way from Elephant & Castle to Swiss Cottage station, tasks 16, **Figure 4.4**). Despite taxi drivers being trained to plan the most direct route between places (see **Chapter 2**), this study focused on natural planning behaviour in experienced drivers who were instructed to plan as they would do on a daily basis, disregarding temporary diversions and obstructions. This might allow other factors to play a role, such as a preference to use major roads and bus lanes, or an early consideration of later obstacles (e.g. which bridge to cross in order to plan around Hyde Park and Regent's Park). Additionally, there is also a possible impact of individual preference for routes based on habits of using particular streets. These habits of using particular streets for certain routes might have been developed over the course of several years of driving a taxi and thus engrained in their planning behaviour. Since taxi drivers were asked to plan naturally, in contrast to planning the shortest route, such an impact of habitually chosen streets cannot be ruled out entirely. However, even these individual preferences require sequential planning across London areas to a particular point and thus may be indicative of hierarchically structured planning.

More structured visualisations of response times along routes that several taxi drivers agreed on allowed identification of sequential variations in mean z-standardised response times across drivers (see **Figure 4.8** and **Supplementary Figure 8.4**). Here, response times varied more along complex routes that involved making mental turns (e.g. task 8, **Figure 4.8c**), along or across boundaries (e.g. Soho) or at potential points of divergence (e.g. Theobald's Road, Trafalgar Square). Such variations of faster and slower responses along routes could highlight that sequences of streets are planned in chunks. For instance, when entering Soho or along Soho's boundaries (task 8, **Figure 4.8**) response times are faster than in sections on or before Shaftesbury Avenue. Such changes in planning speed before entering certain areas and on boundaries agree with the broad predictions from a recent model of hierarchical planning by McNamee and colleagues ([2016](#)).

Model Analysis of Hierarchical Factors

Response times of the route recall were modelled in a basic mixed linear model with taxi drivers and routes as random effects and street network related variables as fixed effects. These variables included agreement rates on London boundaries as found in a previous study (see **Chapter 3**), turning actions, information on road types, the position of a street in the sequence and the Euclidean distance to the goal (**Model 1**). Alternative models, that replaced boundary agreement rates with an entire prominent, distinct London district (**Model 2**) or circuitry, defined as network distance divided by Euclidean distance (**Model 3**) provided additional insight on how potential hierarchical information and other spatial features impact route planning in a real-world environment.

In contrast to prior studies on hierarchical route planning in an artificial environment that relied on strong perceptual differences between districts and thus clear boundaries (e.g. [Wiener & Mallot, 2009](#); [Wiener, Schnee & Mallot, 2004](#); [Schick, Halfmann, Hardiess, Hamm & Mallot, 2019](#)), this study used boundary agreement rates for London districts to closely reflect gradual differences in the perception of real-world boundaries (see **Chapter 3**). Model estimates for these agreement rates indicate that boundaries were recalled faster than streets that were non-boundaries. These boundaries, similar to exchange stations between liens in a transportation network ([Balaguer, Spiers, Hassabis & Summerfield, 2016](#)), impact log-transformed response times between streets as initially predicted. However, instead of supporting the idea of boundaries potentially providing a subgoal structure that would allow for planning ahead for the next area that is being entered and thus associated with slower responses ([Balaguer, Spiers, Hassabis & Summerfield, 2016](#)), the faster recall rather suggests that boundaries are associated with those upcoming areas and planning ahead might occur the step before, or several steps before, as boundaries are being approached. This was also supported by results when boundary agreement rates were replaced by Soho and its boundaries in **Model 2**. Here, a whole distinct district with high boundary agreement rates that was enclosed by the London street network supported more closely initial findings from boundary agreement rates.

Similar to boundaries, the number of streets that remain to be recalled to the destination, significantly impacted on response times, with streets close to the goal named faster than initial streets (cf. **Figure 4.9e**). This was in contrast to findings on hierarchical planning in the transportation network that argued, that in a non-hierarchical, flat

representation the number of steps to the goal would have an impact, but in a hierarchical representation these should not affect response times ([Balaguer, Spiers, Hassabis & Summerfield, 2016](#)). In a large-scale environment like London (UK), the number of streets to the goal however might still reflect complexity effects for long routes regardless of a hierarchical or non-hierarchical representation. Additionally, response time differences with respect to the position of the street in the sequence of streets were predominantly driven by response time differences of initial and final streets rather than the entire sequence (**Figure 4.9e, f**). As taxi drivers disagreed on routes of a particular origin-destination pair, the number of streets even for that particular task varied and a direct comparison was not possible between routes for the same origin destination pair. However, if planning occurred through a tree search ([Streeter & Vitello, 1986](#); [Elliott & Lesk, 1982](#); [Miller & Venditto, 2020](#)), all possible route options to the destination would have to be considered. Such a search would require planning over longer route options initially and shorter route sequences towards the end. Thus, planning times between streets should decrease the closer the named street is to the goal. However, in this study only a comparison of initial and final response times might suggest such an effect (**Figure 4.9e**), but was not observed in general (**Figure 4.9f**). These slower initial response times might reflect a potential comparison of route options at the beginning, whereas faster response times towards the end of the route would not require such planning ahead. Evidence for breadth-first searches has been found by Javadi and colleagues ([2017](#)), who studied planning in Soho with participants novel to that area. Due to this novelty, participants might possibly not have fully developed a hierarchical representation through training that might have impacted their planning. Additionally, the breadth-first search only explained shorter sequences of planning ahead for up to two steps and thus might not emerge from the current data. Furthermore, if longer routes are broken down into shorter sequences of route sections, as a hierarchical representation would suggest, response times should modulate with those sequences, as observed in the current data (**Figure 4.8**). These modulations across shorter sequences for longer routes would be expected to be similar to response time modulations in short routes. Hence differences between initial and final response times should not depend on the number of streets to the goal (**Figure 4.9f**), supporting hierarchical planning. Instead, breadth-first searches and comparison of route options might instead occur during initial planning. This has not been analysed in the current study, because it was not possible to separate these planning actions from other processes occurring during initial planning, which was carried out

silently. Thus, the data on response times between streets might rather support models with hierarchical planning over breadth-first searches that do not emerge in large-scale, real-world environments during route recall.

In contrast to Balaguer and colleagues (2016) it was also not possible to analyse the number of contexts to the goal in the current study, that could have provided additional information on potential hierarchical planning in line with the transportation network. Balaguer and colleagues (2016) studied the hierarchical planning in a linear, clearly distinguishable environment of subway lines. In contrast, the current study was placed in a real-world, higher dimensional environment, where areas instead of subway lines and boundaries instead of intersection were studied. These boundaries underlie gradual differences in perception. Thus, entering the same districts from different directions (e.g. South Bank has clear boundaries at the north and south, but entering from east or west can be conceptually different, see **Section 3.4**) might result in crossing boundaries with different degrees of perception and ultimately impact how clearly areas are perceived along certain boundaries. A preliminary assessment of applying an analysis similar to Balaguer and colleagues (2016) thus suggested that it would be a challenge to conduct and would require further investigation (see *Limitations*).

Model Analysis of Other Spatial Features

In addition to boundaries and areas, other spatial structures related to particular routes, such as turns, road types and distance measures were analysed in the linear mixed model and alternative models.

A major impact of turning actions was found across all three models, where turns into streets were recalled slower than forward actions, in line with other findings that studied the impact of turns on spatial memory (e.g. [Brunec, Ozubko, Ander, Guo, Moscovitch & Barensen, 2020](#)). Mental simulations of turns, especially as an in-street view require more mental resources than actions that do not change the viewpoint. Therefore, the current results are consistent with the notion that taxi drivers visualise their route and mentally simulate travelling along those routes whilst planning. This also aligns with previous observations of the training process (**Section 2.4**). Furthermore, turning actions in this study are also tightly linked to other mental processes, such as decisions of whether a turn is required, where along a road the turn should occur and which options are available. For instance, turning off Shaftesbury Avenue to enter Soho could be achieved through as

Dean St, Wardour St or Great Windmill St. At the same time other options that would violate traffic rules due to one-way systems, such as turning into Greek St, have to be accounted for and disregarded. In line with this are also results highlighting increased response times at individual decision points where route plans diverged between groups of taxi drivers (**Figure 4.10**). These processes put additional load on mental planning that were not considered in many other studies (e.g. [Brunec, Ozubko, Ander, Guo, Moscovitch & Barense, 2020](#)), but could explain why turning actions in the current study have the highest weighting in the model (**Figure 4.9**). Considering such effects of turns and potential ego-centric planning should also be considered for computational models in an artificial intelligence network. Whilst humans seem to rely on exploiting mental visualisations, such simulations might be more difficult to implement in an artificial agent ([Kosslyn, Pinker, Smith & Shwartz, 1979](#)).

Surprisingly, main roads, here conceptualised as trunk and primary roads, were recalled slower than other roads. [Pailhous \(1969; cf. Chase, 1983\)](#) only found differences in how readily Parisian taxi drivers used main and minor roads for their route plans in dependence of their experience, highlighting a greater familiarity and potential salience of major roads. In particular, drivers with less experience preferred the use of major roads, whilst more experienced drivers also exploited the minor road network. However, these findings could be a result of the Parisian qualification process. Drivers in Paris are only required to learn the major street network to qualify and develop knowledge of the minor network later in their career by driving the minor road network (cf. **Section 2.2**). Still, such familiarity and salience effects of major roads are in contrast to current findings as they would be expected to speed up rather than slow down the recall of major street names. However, in contrast to Parisian drivers, London taxi drivers are trained on major and minor road networks to qualify (cf. **Section 2.4**) and develop knowledge and experience across all types of streets in London to ensure they are able to flexibly use the entire network. Therefore, differences in response times are less likely related to familiarity and salience effects, but might be explained through differences in street network properties of major and minor roads. Whilst major roads function as an important link between key areas (cf. [Key:highway, 2020](#)) and span across large distances (e.g. Oxford Street, Shaftesbury Avenue), minor roads often provide local links from nearby areas to major roads (e.g. Dean Street). Hence, major roads, even though potentially more salient in the mental representation, also connect to a larger number of minor roads,

leaving a navigator with more options to consider for their potential route plan, such as potential turns off the major road onto one of the connecting other roads.

In this context, spatial analysis, e.g. space syntax, could provide vital insight on the role of major roads and street network properties for route recall. However, the current approach did not allow for such analysis. Most spatial network analytics use a segment-based approach that segregates entire streets (e.g. Oxford Street) in several segments and attributes spatial measures to each segment, rather than an entire street and their corresponding response times. Additionally, there is currently no approach to automatically assigning segment-based information from the space syntax dataset of London to the street network, as segments were parts of an unlabelled graph (i.e. no assignment of street names) and only contained graph network related information (e.g. betweenness centrality). Future analysis could consider a manual approach and focus on a subset of routes (e.g. task 8) or a specific area (e.g. Soho).

The only spatial variables that had no impact on response times of the response times was Euclidean distance and circuitry (i.e. path distance to the goal divided by Euclidean distance to the goal). Neither the initial model (**Model 1**), nor the alternative model (**Model 2**) found an impact of Euclidean distance to the destination. When Euclidean distance was replaced by circuitry (**Model 3**), there was no impact on route planning response times, contrary to predictions from hierarchical planning in artificial transportation networks ([Balaguer, Spiers, Hassabis & Summerfield, 2016](#)). Whilst a strong effect of having to travel away from the goal (high circuitry) would have been expected, the paths chosen in this study might not have been significant enough to reveal an effect (see **Supplementary Figure 8.5**). In contrast to a transportation network, where U-turns were located close to the goal and required moving away from it, here, detours were modelled through even small deviations from the goal along the path, often also requiring turning actions. These deviations might not have impacted responses as much as turns, which had the strongest impact on response times in the models. Additionally, in this study, taxi drivers were tested, who have years of experience and might be used to navigating detours on a daily basis. Travelling away from the goal might not impact these navigation experts as much as individuals planning routes in an artificial transportation network.

Given that greater distances are often associated with higher planning demands as planning has to be carried out across a larger number of potential places, i.e. states (e.g. [Streeter & Vitello, 1986](#); [Elliott & Lesk, 1982](#); [Miller & Venditto, 2020](#)), why did

Euclidean distance not impact the route planning demands? It seems plausible that spatial compression (e.g. [Bonasia, Blommestejn & Moscovitch, 2016](#)), the number of streets to the goal, or the subgoal effect of boundaries, could have outweighed the impact of distance. This would support hierarchical planning as a spatial segregation that triggers sequential planning of shorter route sections would outweigh planning along the entire space and distance. It is worth noting that in many routes Euclidean distance might predict planning times as it will be in many cases correlated with the number of streets to the goal. Here, the study was set up specifically to decorrelate these metrics allowing a distinction. A small, but significant effect of streets to the goal was observed for planning demands.

Other Correlates and Confounds

Other potentially confounding factors, such as age, experience or linguistic factors, were not found to impact response times. For the entire group of taxi drives, age and experience were correlated and as age increase, so did experience. Whilst age would be expected to impair route planning (e.g. [van der Ham & Claessen, 2020](#)), experience should have the opposite effect (e.g. [Pailhous, 1969](#); [Chase, 1983](#)). Thus, for the entire group of taxi drivers these factors might have cancelled out any response time related effects. However, even for a subset of drivers, where age and experience were decorrelated, no impact of age or experience was found. Training of spatial navigation abilities is expected to cause changes in the hippocampal volume (e.g. [Maguire, Gadian, Johnsrude, Good, Ashburner, Frackowiak & Frith, 2000](#); [Maguire, Nannery & Spiers, 2006](#)), the neural centre for spatial navigation. Volume changes in the posterior hippocampus were correlated with experience and thus, with greater experience one might expect better performance. However, the current data of neither the entire group nor the subset support these findings as there were no correlations found between experience and response times. It is possible that training protects against age related deterioration of spatial skills ([Lövdén, Schaefer, Noack, Bodammer, Kühn, Heinze, Düzel, Bäckman, & Lindenberger, 2012](#)). This might in particular affect London taxi drivers' route planning as it prevents from age related effects as they train and use their spatial navigation skills on a daily basis to navigate in London. Ultimately, this might explain, why neither the entire group, nor the subset of taxi drivers showed any aging effects for response times of route recalls.

Additionally, whilst Parisian taxi drivers indicate experience related differences in route planning ([Pailhous, 1969](#); [Chase, 1983](#)), London taxi drivers do not. This could also be potential result of training differences between Parisian and London taxi drivers. Thus it can be argued that different levels of experience can only account for performance differences up to a certain point of knowledge acquisition. At early stages, where spatial knowledge is incomplete, e.g. inexperienced Parisian drivers who only learned the major street network, experience can contribute to knowledge acquisition. However, when a certain point of familiarity with the entire street network is reached, further experience might only help with maintaining knowledge, but not expand it. For London taxi drivers, this point could be reached earlier as their qualification process requires them to demonstrate exceptional knowledge of the entire London street network (**Chapter 2**), explaining why there might be no impact of experience on response times during route planning.

From a linguistic perspective, it could be argued that the complexity of street names may interfere with response times during the verbal recall. In this study, we limited linguistic analysis to test a potential correlation between the number of letters and response times. Longer street names (e.g. Great Marlborough Street vs Pall Mall) were expected to potentially affect recall speed as they are mentally processed for verbalisation and thus cause a delay before such a street was named. However, no such effect was found. Still, this approach might not entirely reflect potential word complexity or pronunciation difficulties that might occur and impact on responses. Additional linguistic analysis of these effects might be needed in future studies, but these approaches went beyond the scope of this study.

Predicting Hierarchical Planning

This study has provided important insight into which factors impact spatial planning in a real-world environment based on ecologically valid data. Here, particularly the effect of mentally perceived spatial, street network boundaries was studied to understand a potential spatial segregation of an urban city and hierarchical planning. However, these were limited to a popular and distinct London district. For other areas these effects were not studied and might be less prominent due to weaker perception of boundaries. Other factors, such as main roads and turns, or points in the street network that require decisions over alternative options slow down route planning.

In this context, interesting patterns emerged from a range of variables, but specific evidence for hierarchies, as within a strongly controlled environment with transportation networks ([Balaguer, Spiers, Hassabis & Summerfield, 2016](#)), is not as clear in the current study. In general, boundaries and an entire district (i.e. Soho) were found to be processed faster and provide support for hierarchical planning that are in contrast with other lengthy search structures, such as breadth-first search ([Streeter & Vitello, 1986](#); [Elliott & Lesk, 1982](#); [Miller & Venditto, 2020](#)). Shorter breadth-first search structures might still prevail ([Javadi, Emo, Howard, Zisch, Yu, Knight, Silva & Spiers, 2017](#)) and a directional limitation of search options based on a vector to the goal might prune search options to a small set of streets ([Banino et al., 2018](#)). The comparison between initial and final responses of the recall process found slower planning initially. This could also indicate a higher initial search demand at stages where options have to be weight against each other. However, as these do not scale with the total number of steps, later stages could exploit a segregation of the route and segmented planning by using boundaries as subgoals (**Chapter 2**), indicating a hierarchical planning structure. This was specifically supported by faster response times on boundaries (and within Soho) and consistent with Balaguer and colleagues ([2016](#)).

It remains open how these variables can be interpreted and used to predict route planning at places, where multiple features combine and interfere in their effects. For instance, Shaftesbury Avenue in task 8 (**Figure 4.8**) was recalled later during the route sequence and is a boundary that should attribute it to Soho. Thus, it should be predicted to be recalled fast. However, the response time for Shaftesbury Avenue to be recalled in the sequence is extremely high. It appears that the main road character and turning action (coming from Charing Cross Road) outweigh these factors. Additionally, the intersection of Charing Cross Road with Shaftesbury Avenue might give it the character of a decision point, as both roads are main roads and several alternative options have to be considered, e.g. whether to cut through the north eastern corner of the area of Leicester Square (Task 8, **Figure 4.4**) and where to enter Soho from Shaftesbury Avenue to optimally reach the destination.

Thus, forming predictions for a complex, real-world environment have to be carefully considered with respect to many factors that might impact planning at specific places. Still, these results provide real-world approach not only to hierarchical planning, but to route planning in general and an extension to other approaches in behavioural and

neuroscientific research, as well as modelling approaches that use artificial agents to explain real-world navigation behaviour.

Limitations

In this study, a total of 43 taxi drivers was tested across two sets of data collection in the area of Bloomsbury and Kings Cross. Tasks partially differed across collection times to allow testing of a range of route properties without risking fatigue effects of drivers (except for task 7 and 8 to allow for comparison across groups). Even though a larger sample size for each of the two collection times would have allowed better analysis of some effects (e.g. greater sample might have allowed an analysis across more divergence points), a total of almost 3,400 response times between streets was analysed in this study in relation to different street network properties. This data already allowed to identify interesting effects in the route planning process of licensed London taxi drivers, such as the impact of turns or road type. Of specific interest was the impact of perceived street network related boundaries based on agreement rates and emerged in a natural, urban setting rather than an artificial environment. The collected data already managed to highlight such an impact. However, drivers showed preferences of working in Central London, which could have impacted their knowledge on areas with greater distance to central London (e.g. West London, south of the River Thames). Extended testing across London at different taxi ranks, might have better reflected general tendencies across the entire city.

Even though the study included several geo-spatial properties (e.g. distance measures, boundaries, road types, turns), there is a range of information that was not accounted for in the current analysis. For instance, planning directions (planning from West to East in task 7, Westway to Old Street Station), angular deviations at each street, spatial analytics or perceptual input of building use (e.g. shops, industrial or residential) were not or only marginally (i.e. angular deviation and circuitry are related) included. Here, these variables went beyond the scope of the study, but should be considered in the future.

Methodologically, it can be argued that only verbal data had been collected in this study. Even though a preliminary linguistic analysis of word counts indicated no linguistic impact, other factors, such as word complexity or familiarity of street names have not been accounted for. Taxi drivers might be aware of a street, but find it more difficult to recall the street by name. Additional validation of findings could be achieved

through alternative approaches with designs that do not rely on verbal recall of street names. For instance, video recorded route drawings on maps could provide supporting evidence for the current results. However, such a design would draw less on mental representations as visual features of the map (differently highlighted routes) might impact route planning as external spatial information would be available. To avoid such an impact, study designs might have to restrict visual information to a small area around the streets that are being highlighted (e.g. only an area smaller than a quarter mile on a map is visible at any time) to ensure planning to rely on mental planning. Implementing such a study might however require technical or technological approaches that could come with other drawbacks regarding motor actions and a preference for paper maps over digitised maps with taxi drivers.

Alternatively, drivers might be prompted to only highlight key points that they would pass through on a map or indicate if specific streets would be part of their route. Under time pressure, these prompts might highlight response time differences for street network structures that are part of a hierarchical representation when contrasted with streets that are non-hierarchical. Here, planning would have to depend on pre-defined conditions, such as the most direct route rather than general preferences as in this study. However, such approaches would not allow for rich information on street level, but focus on coarse route level information instead as attention is drawn to key points rather than entire routes.

Conclusion

The current study provided a real-world approach to test with ecologically valid data how street network properties and in particular a potential hierarchical mental representation of the environment impacts on route planning in London taxi drivers. In contrast to other approaches in virtual environments with clearly distinguishable areas and a visually prominent hierarchy, the current study used less obvious, mental boundaries, which underlie a gradual perception based on agreement rates. This perception was found to impact on responses during route recall. However, other factors, such as turning actions or road types also impact route planning, whereas distance measures do not. Taken together, these results support a potential exploitation of hierarchies during route planning.

5. GENERAL DISCUSSION

Forming a representation of complex, urban spaces and using this knowledge to move around an environment is an ability that humans often exploit consciously and unconsciously on a daily basis. It requires individuals to familiarise themselves with a novel environment, make sense of its structure, understand relations and connections between places and ultimately form plans that allow them to reach a destined place within an environment. This place could be a room in a house, a park in the neighbourhood or a friend at the other end of a metropolitan area. Learning, representing and exploiting information of a space are important aspects of navigation that enable humans to carry out such activities successfully and have been individually studied in various settings. Here, these aspects were brought together in three approaches under natural conditions and with real-world relevance for London taxi drivers, who are trained navigation experts even beyond the Central London street network. To understand their learning process, information from training school material, lessons and an interview with a teacher were collected and observations reported. Novel approaches were used to collect and analyse ecologically valid data of their mental representations of the complex London street network and the ways their route planning exploits this representation.

Overview of Key Findings

Learning of the Knowledge of London, as done by students in Knowledge schools, relies on a combination of map-based studies and experienced, in-situ travelling of London areas. Theoretical knowledge covers specific knowledge of the location of points of interest, the street network including street names, traffic rules and the ability to give exact driving instructions. These are acquired through a variety of strategies (see **Table 2.1**) that use short routes (i.e. *runs*) that systematically connect origin-destination pairs spread across London and form a dense network of overlapping and interconnecting routes. Like a jigsaw puzzle, small parts of London are learned to prevent demotivation and support optimal coverage of the entire area, which is also supported by the stepwise examination process that becomes more rigorous the further students proceed.

Street network boundaries, in contrast to many conceptual and experimental expectations, were found to reflect a spectrum of agreement. Consensus on which streets counted as boundaries for an area ranged from no consensus with a wide spread disagreement across streets (e.g. the City of London, Leicester Square) to a high

consensus on particular streets across all drivers. These highly agreed boundaries showed commonalities in terms of district properties (i.e. topical distinct, popular districts), street network properties (i.e. main roads, near rectangular and regularly shaped) and geographical properties (e.g. major parks).

The route recall was based on training and examination procedures of taxi drivers and allowed novel insight on street level planning rather than focusing on entire routes. Initial visualisation of routes indicated a task dependent agreement, where linear routes were more likely to reflect high agreement than routes that required more decisions on avoiding obstacles (e.g. parks, crossing bridges) or taking turns. Linear mixed models highlighted that turns and main roads came with a planning cost, while boundaries (or an entire district like Soho) facilitated planning, but distance and travelling away from the goal did not affect route planning. These findings showed a pattern in line with other findings that supported hierarchical planning, but specific evidence in this first approach using a real-world setting cannot be assumed so far and leaves room for future research.

Learning the Knowledge, Mental Representations and Route Recall

London taxi drivers are capable of locating places of interest and flexibly navigating between them. By doing so, they can take customer specifications into account that might relate to the shortest, fastest, most panoramic, or least congested route and account for additional stops and modifications as well as avoiding main roads and traffic lights. Such flexible planning can hardly be achieved through experience alone as a lack of knowledge in the general population, even amongst the most experienced London travellers, shows. Instead, it is the result of extreme expectations and rigorous training on the Knowledge of London to meet those expectations (**Chapter 2**). It requires the learning of the street network within the six-mile radius around Charing Cross and starts with learning the most important route connections of 26,000 streets between the 360 origin-destination of the Blue Book, which is later extended to cover the entire street network beyond those initial arteries. Acquiring a mental representation of such an enormous area, with detailed knowledge about street names, traffic rules and the precise location of places is worldwide unique. This provides ample opportunities to study spatial navigation in individuals with a near perfect knowledge on street-level that could not be expected from non-taxi drivers, even in a small-scale environment, such as a familiar neighbourhood. The level of detailed knowledge and experience that taxi drivers provide across central areas of London

allowed to study tendencies of perceived boundaries that were related to the street network. Inspired by their training and examination process, further testing of the route recall process for specifically chosen origin-destination pairs was also possible.

The training process by which such knowledge is achieved even nowadays relies mainly on a combination of theoretical map studies and practical in-situ visits of theoretically studied places. The transition from theoretical to practical knowledge is facilitated through specifically prepared learning material and learning strategies to facilitate learning and prevent misconceptions. However, it is also possible that the learning process, and in particular the material and the strategies used, impact the mental representation that taxi drivers gain of London. For instance, organising the Blue Book around 360 origin-destination pairs and their quarter-miles facilitates chunking, but could also give rise to a different hierarchical segregation of London around specific anchor points. Even though such a representation is similar unlikely to prevail as there was no obvious evidence from boundary drawings, certain Blue Book points, such as Manor House Station and Gibson Square (even if not all), might unconsciously still be more salient than other points. These might impact or even drive the choice of marker points (e.g. 50% and 75% bullets) along a route and thus a segmentation of that route. Alternatively, if marker points are really independently chosen of prominent Blue Book locations, they might carry important information about potential hierarchical representations that taxi drivers might not perceive consciously. For instance, bridges were highlighted by the knowledge school teacher as prominent markers for routes that crossed the River Thames (**Chapter 2**), but the river itself was not perceived as a geographical boundary with high agreement across all taxi drivers (**Chapter 3**). Other such points chosen across the street network might highlight different patterns unconscious structures that taxi drivers might agree on with different rates, similar to boundaries. These might be worth exploring in the future.

Similar to Blue Book points and marker points, map features might drive the mental representations that taxi drivers use for route planning. Here, especially the ‘oranges and lemons’, the major roads marked in orange and yellow on a map, were expected to have an impact as previous findings with Parisian taxi drivers ([Pailhous 1969](#); [Chase, 1983](#)) suggested. Even though boundaries were mainly placed along main roads, not all main roads were attributed with a boundary effect. Still, when taxi drivers rely on map-based information for their route planning, these visually highlighted roads might be more prominent and salient and might more readily add to unconscious effects of a potential

segregation. Slower response times during the route recall of main roads might point towards such an alternative segregation, as more travelling options have to be accounted for on these roads. Similar effects might not be found if the general population was tested, as they might not perceptually differentiate between road types, mainly due to a lack of map studies. In this context, it would be interesting to see if training of taxi drivers on maps that visually highlight different features (e.g. district boundaries instead of main roads) would impact their representation and potentially support a segregation of the environment, similar to findings in previous studies in a controlled virtual reality environment (e.g. [Wiener & Mallot, 2009](#); [Wiener, Schnee & Mallot, 2004](#); [Schick, Halfmann, Hardiess, Hamm & Mallot, 2019](#)). Maps with such a visual segregation (e.g. districts) might ultimately facilitate route planning behaviour and support learning strategies, such as bullet pointing and recall training on straight street sequences that span across long distances. However, the optimal choice of such a visual segregation might be more challenging as districts alone do not seem to facilitate a boundary representation and the example of the irregularly defined boundaries of the City of London showed (**Chapter 3**). Here, a more balanced approach between defined and desired boundaries supportive of route planning might have to be taken.

Mental visualisations during the route recall are another aspect of the training that might impact the route planning process. As experience grows through in-situ visits, students are trained to use episodic memories of travelling quarter-mile areas or flowing and connecting runs in London to mentally visualise those locations, identify places and mentally travel along the route. The impact of turning events on response times supports such mental visualisations of the route as turns were found to come with a higher cognitive load. This ability, based on high familiarity from repeated travelling of Blue Book runs and quarter-mile areas, seems to outperform other ways of route planning, that rely on a map-based view of the environment. Initially, such a map-based internalisation of London is trained to promote optimal routes along the direct line, prevent from biases or and misconceptions or support other route specific requirements an examiner might request. However, during navigation, a transitions from a map-based plan to travelling with in-street view in an real-world environment might come with even higher costs than in-street visualisations of potential turns (e.g. [Ishikawa & Kiyomoto, 2008](#)). Map-based knowledge might thus facilitate efficient choices for in-street view navigation. Having studied the Blue Book runs, planned new routes across London linking the Blue Book runs efficiently on the map and then having travelled them multiple times, will allow taxi

drivers to rely on those experiences for similar destinations without having to rely on map-based knowledge. This could be key to transforming map-based knowledge into efficient use of in-street view knowledge during route planning. The option to exploit detailed map-based information for route planning still remains.

More research is needed to understand these connections and how specific aspects of the taxi driver training process ultimately affect mental visualisations and the route planning. This understanding might ultimately not only improve the training process of taxi drivers, but also impact positively on how humans navigate in a wider sense.

Boundary Perception and Route Planning with Non-Experts

As taxi drivers learn to build their mental map of places and the street network in London to be able to flexibly navigate, their representation might be shaped by factors of their learning process. Individuals, who build their mental maps naturally through experience and navigation aids, might - even on a small scale - build a different representation of their environment. This representation could be influenced more by individual experiences of places of importance. Streets that they travel often on the way to work or a friend's house could perceptually gain importance, similar to boundary streets and perceptually separate less important or familiar areas from each other. This way, even within a neighbourhood, individuals build a more fragmented knowledge of their environment that could differ across individuals for the same area (cf. [Stansfeld, 2019](#)). On more popular and distinct areas, such as Soho and parks, taxi driver and non-taxi driver perception might overlap more closely and reflect similar tendencies for non-experts.

Other geographical structures, such as the river Thames, might be more prominent in the mental representation of an urban environment of individuals. These might serve as important anchor and orientation points for route planning that taxi drivers do not need as a result of their knowledge of London. Whilst taxi drivers can exploit various local landmarks for self-orientation or to locate places of interest in relation to these landmarks, imperfect knowledge of individuals would restrict them in their choice of cues. Instead, an approximate awareness of the course of the River Thames running east to west might be more helpful for individuals, in Covent Garden aiming to visit St Paul's east of their location. These structures might ultimately lead to a differently accentuated boundary

representation for non-taxi drivers. How these perceptions ultimately impact route planning in both populations still remains an open question.

It would be interesting to understand these processes in more detail and compare expert and non-expert perception. However, testing with the general population would be more challenging and require novel approaches that even taxi drivers might not be familiar with to ensure comparability. These approaches could use gamified navigation tasks in form of an online game or mobile application that individuals and taxi drivers could download. Alternatively, eye tracking during map use might provide additional support or highlight differences to current findings.

In a wider sense, these findings could improve various areas of life of individual and entire groups of navigators. Understanding how individuals use spatial knowledge from maps or directly derived from the environment to build their own mental representations or plan routes, can impact how maps and GPS technology are designed. Here, specific features, visual highlights and the quality and quantity of provided information could be optimised to support a specific use. Regionalised maps of London could support hierarchical representations, a more efficient segregation and faster learning of the knowledge for taxi drivers or highlight a more structured approach to understand London areas in general. Urban planning and traffic control could profit from understanding tendencies of how districts and street network structures are perceived and planned to be travelled. The street network of future cities could be designed to serve a particular purpose and allow easy memorability and travelling. Planning on how traffic is directed or redirected in certain areas could be optimised or improved based on factors that impact human route planning. Along boundaries, where planning and potential reactions are faster, other requirements might apply than for main roads with decision points and areas that require several turns and thus might slow down traffic flow. GPS devices and instruction-based navigation could adapt learning strategies to support a better understanding of and connection with the environment an individual is travelling in. Involving users of navigation devices in the route planning process and facilitating the use of navigation strategies that have proven to work for taxi drivers might enable them to learn and make better sense of their environment. Ultimately, such training might prevent from the deteriorating effects current navigation devices have on human navigation abilities or even impact the onset of dementia.

Beyond these applications related to navigation, that show how taxi drivers are trained to better connect with their environment and use this understanding for route planning

purposes, the findings also provide insight in the ways humans hierarchically process and cluster information to make decisions in general. This can involve simple daily life actions, such as ‘making a cup of tea’, which can be broken down into ‘heating water’, ‘taking a mug out of the cupboard’, ‘putting in a tea bag’ and ‘adding the hot water’, and planning and optimising a series of actions that require making choices (e.g. first, doing the laundry, then cleaning the house and finally, when the washing machine is finished, hanging the washing, cf. [Pezzulo, Rigoli & Friston, 2018](#)), or abstract information clusters, such as accessing information stored on a computer. Computational approaches (e.g. [McNamee, Wolpert & Lengyel, 2016](#)) could use this information to learn from taxi drivers’ route planning in London to better understand these and many other hierarchical planning structures that humans carry out in daily life.

This work only addressed a few of these questions and provided initial findings on learning, mental representations and route planning in a real-world, urban environment. Hopefully future research will build on these findings and extend ideas outlined in this work.

6. REFERENCES

- A to Z from Collins - The Knowledge (2020). Retrieved from <https://collins.co.uk/pages/the-knowledge>
- Arnold, A. E., Iaria, G., & Ekstrom, A. D. (2016). Mental simulation of routes during navigation involves adaptive temporal compression. *Cognition*, *157*, 14-23. DOI: doi.org/10.1016/j.cognition.2016.08.009
- Astur, R. S., Germain, S. A. S., Baker, E. K., Calhoun, V., Pearlson, G. D., & Constable, R. T. (2005). fMRI hippocampal activity during a virtual radial arm maze. *Applied psychophysiology and biofeedback*, *30*(3), 307-317. DOI: doi.org/10.1007/s10484-005-6385-z
- Audacity [Computer software]. (2020). Retrieved from <https://www.audacityteam.org/>
- Badre, D., Kayser, A. S., & D'Esposito, M. (2010). Frontal cortex and the discovery of abstract action rules. *Neuron*, *66*(2), 315-326. DOI: doi.org/10.1016/j.neuron.2010.03.025
- Balaguer, J., Spiers, H., Hassabis, D., & Summerfield, C. (2016). Neural mechanisms of hierarchical planning in a virtual subway network. *Neuron*, *90*(4), 893-903. DOI: doi.org/10.1016/j.neuron.2016.03.037
- Banino, A., Barry, C., Uria, B., Blundell, C., Lillicrap, T., Mirowski, P., Pritzel, A., Chadwick, M. J., Degris, T., Modayil, J., Wayne, G., Soyer, H., Viola, F., Zhang, B., Goroshin, R., Rabinowitz, N., Pascanu, R., Beattie, C., Petersen, S., Sadik, A., Gaffney, S., King, H., Kavukcogly, K., Hassabis, D., Hadsell, R. & Kumaran, D. (2018). Vector-based navigation using grid-like representations in artificial agents. *Nature*, *557*(7705), 429-433. DOI: doi.org/10.1038/s41586-018-0102-6
- Barry, C., & Burgess, N. (2014). Neural mechanisms of self-location. *Current Biology*, *24*(8), R330-R339. DOI: doi.org/10.1016/j.cub.2014.02.049
- Bast, H., Delling, D., Goldberg, A., Müller-Hannemann, M., Pajor, T., Sanders, P., Wagner, D., & Werneck, R. F. (2016). Route planning in transportation networks. In *Algorithm engineering* (pp. 19-80). Springer, Cham. DOI: doi.org/10.1007/978-3-319-49487-6_2
- Battersby, S. E., & Montello, D. R. (2009). Area estimation of world regions and the projection of the global-scale cognitive map. *Annals of the Association of American Geographers*, *99*(2), 273-291. DOI: doi.org/10.1080/00045600802683734

- Baumann, O., & Mattingley, J. B. (2010). Medial parietal cortex encodes perceived heading direction in humans. *Journal of Neuroscience*, *30*(39), 12897-12901. DOI: doi.org/10.1523/JNEUROSCI.3077-10.2010
- Beason, R. C., Wiltschko, R., & Wiltschko, W. (1997). Pigeon homing: effects of magnetic pulses on initial orientation. *The Auk*, *114*(3), 405-415. DOI: doi.org/10.2307/4089242
- Bellmund, J. L., de Cothi, W., Ruiter, T. A., Nau, M., Barry, C., & Doeller, C. F. (2019, October). [Distorting the metric of cognitive maps deforms memory](#). In *49th Annual Meeting of the Society for Neuroscience (SfN)*.
- Bomba, P. C., & Siqueland, E. R. (1983). The nature and structure of infant form categories. *Journal of Experimental Child Psychology*, *35*(2), 294-328. DOI: [doi.org/10.1016/0022-0965\(83\)90085-1](https://doi.org/10.1016/0022-0965(83)90085-1)
- Bonasia, K., Blommestejn, J., & Moscovitch, M. (2016). Memory and navigation: Compression of space varies with route length and turns. *Hippocampus*, *26*(1), 9-12. DOI: doi.org/10.1002/hipo.22539
- Bottom, D. L., Jones, K. K., Cornwell, T. J., Gray, A., & Simenstad, C. A. (2005). Patterns of Chinook salmon migration and residency in the Salmon River estuary (Oregon). *Estuarine, Coastal and Shelf Science*, *64*(1), 79-93. DOI: doi.org/10.1016/j.ecss.2005.02.008
- Botvinick, M. M., Niv, Y., & Barto, A. G. (2009). Hierarchically organized behavior and its neural foundations: a reinforcement learning perspective. *Cognition*, *113*(3), 262-280. DOI: doi.org/10.1016/j.cognition.2008.08.011
- Broach, J., Dill, J., & Gliebe, J. (2012). Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transportation Research Part A: Policy and Practice*, *46*(10), 1730-1740. DOI: doi.org/10.1016/j.tra.2012.07.005
- Browne, C. B., Powley, E., Whitehouse, D., Lucas, S. M., Cowling, P. I., Rohlfshagen, P., Tavener, S., Perez, D., Samothrakis, S., & Colton, S. (2012). A survey of Monte Carlo tree search methods. *IEEE Transactions on Computational Intelligence and AI in games*, *4*(1), 1-43. DOI: doi.org/10.1109/TCIAIG.2012.2186810
- Brunec, I. K., Javadi, A. H., Zisch, F. E., & Spiers, H. J. (2017). Contracted time and expanded space: The impact of circumnavigation on judgements of space and time. *Cognition*, *166*, 425-432. DOI: doi.org/10.1016/j.cognition.2017.06.004
- Brunec, I. K., Ozubko, J. D., Ander, T., Guo, R., Moscovitch, M., & Barense, M. D. (2020). Turns during navigation act as boundaries that enhance spatial memory and

- expand time estimation. *Neuropsychologia*, 107437. DOI: doi.org/10.1016/j.neuropsychologia.2020.107437
- Büchner, S., Hölscher, C., & Strube, G. (2007, May). [Path choice heuristics for navigation related to mental representations of a building](#). In *Proceedings of the European Cognitive Science Conference* (pp. 504-509).
- Burris, C. T., & Branscombe, N. R. (2005). Distorted distance estimation induced by a self-relevant national boundary. *Journal of Experimental Social Psychology*, 41(3), 305-312. DOI: doi.org/10.1016/j.jesp.2004.06.012
- Byrne, R. W. (1979). Memory for urban geography. *The Quarterly Journal of Experimental Psychology*, 31(1), 147-154. DOI: doi.org/10.1080/14640747908400714
- Campari, I. (1996). [Uncertain boundaries in urban space](#). *Geographic objects with indeterminate boundaries*, 2, 57-69.
- Chase, W. G. (1983). Spatial representations of taxi drivers. In *The acquisition of symbolic skills* (pp. 391-405). Springer, Boston, MA. DOI: doi.org/10.1007/978-1-4613-3724-9_43
- Chen, L. L., Lin, L. H., Green, E. J., Barnes, C. A., & McNaughton, B. L. (1994). Head-direction cells in the rat posterior cortex. *Experimental brain research*, 101(1), 8-23. DOI: doi.org/10.1007/BF00243212
- Chrastil, E. R., & Warren, W. H. (2014). From cognitive maps to cognitive graphs. *PloS one*, 9(11), e112544. DOI: doi.org/10.1371/journal.pone.0112544
- Colgin, L. L., Moser, E. I., & Moser, M. B. (2008). Understanding memory through hippocampal remapping. *Trends in neurosciences*, 31(9), 469-477. DOI: doi.org/10.1016/j.tins.2008.06.008
- Coluccia, E., & Louse, G. (2004). Gender differences in spatial orientation: A review. *Journal of environmental psychology*, 24(3), 329-340. DOI: doi.org/10.1016/j.jenvp.2004.08.006
- Constantinescu, A. O., O'Reilly, J. X., & Behrens, T. E. (2016). Organizing conceptual knowledge in humans with a gridlike code. *Science*, 352(6292), 1464-1468. DOI: doi.org/10.1126/science.aaf0941
- Costa, M., & Bonetti, L. (2018). Geometrical distortions in geographical cognitive maps. *Journal of Environmental Psychology*, 55, 53-69. DOI: doi.org/10.1016/j.jenvp.2017.12.004
- Coughlan, G., Coutrot, A., Khondoker, M., Miniñane, A. M., Spiers, H., & Hornberger, M. (2019). Toward personalized cognitive diagnostics of at-genetic-risk Alzheimer's

- disease. *Proceedings of the National Academy of Sciences*, 116(19), 9285-9292. DOI: doi.org/10.1073/pnas.1901600116
- Coughlan, G., Coutrot, A., Khondoker, M., Minihane, A., Spiers, H., & Hornberger, M. (2018). Impact of sex and APOE status on spatial navigation in pre-symptomatic Alzheimer's disease. bioRxiv, 287722. DOI: doi.org/10.1101/287722
- Coutrot, A., Patai, E., Silva, R., Manley, E., Weiner, J., Dalton, R., Hoelscher, C., & Spiers, H. (2018, November). [Cities have a negative impact navigation ability: Evidence from mass online assessment via Sea Hero Quest](#). In *Society for Neuroscience*.
- Coutrot, A., Schmidt, S., Coutrot, L., Pittman, J., Hong, L., Wiener, J. M., Hoelscher, C., Dalton, R.C., Hornberger, M., & Spiers, H. J. (2019). Virtual navigation tested on a mobile app is predictive of real-world wayfinding navigation performance. *PloS one*, 14(3). DOI: doi.org/10.1371/journal.pone.0213272
- Coutrot, A., Silva, R., Manley, E., De Cothi, W., Sami, S., Bohbot, V. D., Wiener, J.M., Hoelscher, C., Dalton, R.C., Hornberger, M., & Spiers, H. J. (2018). Global determinants of navigation ability. *Current Biology*, 28(17), 2861-2866. DOI: doi.org/10.1016/j.cub.2018.06.009
- Dahmani, L., & Bohbot, V. D. (2020). [Habitual use of GPS negatively impacts spatial memory during self-guided navigation](#). *Scientific Reports*, 10(1), 1-14.
- Dakin, R. J. (1965). A tree-search algorithm for mixed integer programming problems. *The computer journal*, 8(3), 250-255. DOI: doi.org/10.1093/comjnl/8.3.250
- Daw, N. D., Gershman, S. J., Seymour, B., Dayan, P., & Dolan, R. J. (2011). Model-based influences on humans' choices and striatal prediction errors. *Neuron*, 69(6), 1204–1215. DOI: doi.org/10.1016/j.neuron.2011.02.027
- de Cothi, W. J. (2020). *Predictive maps in rats and humans for spatial navigation* (Doctoral dissertation, UCL (University College London)). <https://discovery.ucl.ac.uk/id/eprint/10099051/>
- Doeller, C. F., Barry, C., & Burgess, N. (2010). Evidence for grid cells in a human memory network. *Nature*, 463(7281), 657-661. DOI: doi.org/10.1038/nature08704
- Dyer, F. C., & Could, J. L. (1983). [Honey bee navigation: the honey bee's ability to find its way depends on a hierarchy of sophisticated orientation mechanisms](#). *American Scientist*, 71(6), 587-597.
- Ekstrom, A. D., Kahana, M. J., Caplan, J. B., Fields, T. A., Isham, E. A., Newman, E. L., & Fried, I. (2003). Cellular networks underlying human spatial navigation. *Nature*, 425(6954), 184-188. DOI: doi.org/10.1038/nature01964

- Ekstrom, A. D., Spiers, H. J., Bohbot, V. D., & Rosenbaum, R. S. (2018). Human spatial navigation. Princeton University Press. ISBN: [9780691171746](#)
- Eleanor Cross Knowledge School. (2017). Blue Book 320 Runs Only [PDF file]. Retrieved from <http://eleanorcross.net/store/>
- Electronic blue book - a Freedom of Information request to Transport for London. (2019, January 2). Retrieved from https://www.whatdotheyknow.com/request/electronic_blue_book and <https://www.whatdotheyknow.com/request/89944/response/219108/attach/3/Blue%20Book%20All%20London%20no%20cover.pdf>
- Elliott, R. J., & Lesk, M. (1982). [Route Finding in Street Maps by Computers and People](#). In *AAAI* (Vol. 82, pp. 258-261).
- English Heritage. (n.d.). History of London Wall. Retrieved June 15, 2020 from <https://www.english-heritage.org.uk/visit/places/london-wall/History/>
- Epstein, D. G. (1973). [Brasília, plan and reality: a study of planned and spontaneous urban development](#). Univ of California Press.
- Federación Profesional del Taxi de Madrid: Departamento de Formación. (2010, April, 15). Retrieved from <https://www.fptaximadrid.es/index.php/formacion>
- Fennema, E., & Sherman, J. (1977). Sexual stereotyping and mathematics learning. *The Arithmetic Teacher*, 24(5), 369-372. Retrieved May 20, 2020, from www.jstor.org/stable/41189301
- Filomena, G., Verstegen, J. A., & Manley, E. (2019). A computational approach to ‘The Image of the City’. *Cities*, 89, 14-25. DOI: doi.org/10.1016/j.cities.2019.01.006
- Frankenstein, J., Mohler, B. J., Bühlhoff, H. H., & Meilinger, T. (2012). Is the map in our head oriented north?. *Psychological science*, 23(2), 120-125. DOI: doi.org/10.1177/0956797611429467
- Franks, N. R., & Fletcher, C. R. (1983). Spatial patterns in army ant foraging and migration: *Eciton burchelli* on Barro Colorado Island, Panama. *Behavioral Ecology and Sociobiology*, 12(4), 261-270. DOI: doi.org/10.1007/BF00302894
- Franz, M. O., Schölkopf, B., Mallot, H. A., & Bühlhoff, H. H. (1998). Where did I take that snapshot? Scene-based homing by image matching. *Biological Cybernetics*, 79(3), 191-202. DOI: doi.org/10.1007/s004220050470
- Full Set of Blue Book. (2020, 6 May). Retrieved from <https://www.taxitradepromotions.co.uk/green-badge-blue-book-runs/10002.25.html>

- Gardony, A. L., Brunyé, T. T., Mahoney, C. R., & Taylor, H. A. (2013). How navigational aids impair spatial memory: Evidence for divided attention. *Spatial Cognition & Computation*, 13(4), 319-350. DOI: doi.org/10.1080/13875868.2013.792821
- GeoJSON. (n.d.). Retrieved June 02, 2020, from <https://doc.arcgis.com/en/arcgis-online/reference/geojson.htm>
- Gershman, S. J., Horvitz, E. J., & Tenenbaum, J. B. (2015). Computational rationality: A converging paradigm for intelligence in brains, minds, and machines. *Science*, 349(6245), 273-278. DOI: doi.org/10.1126/science.aac6076
- Gillner, S., & Mallot, H. A. (1998). Navigation and acquisition of spatial knowledge in a virtual maze. *Journal of cognitive neuroscience*, 10(4), 445-463. DOI: doi.org/10.1162/089892998562861
- Giocomo, L. M., Stensola, T., Bonnevie, T., Van Cauter, T., Moser, M. B., & Moser, E. I. (2014). Topography of head direction cells in medial entorhinal cortex. *Current Biology*, 24(3), 252-262. DOI: doi.org/10.1016/j.cub.2013.12.002
- Giraud, M. D., & Peruch, P. (1988). Représentation de l'espace urbain et potentiel d'activité du chauffeur de taxi.
- Giraud, M. D., & Peruch, P. (1988). Spatio-temporal aspects of the mental representation of urban space. *Journal of Environmental Psychology*, 8(1), 9-17. DOI: [doi.org/10.1016/S0272-4944\(88\)80020-3](https://doi.org/10.1016/S0272-4944(88)80020-3)
- Gladwin, T. 1970. East is a big bird: Navigation and logic on Puluwat Atoll. Cambridge, MA: Harvard University Press. DOI: doi.org/10.2307/j.ctvj5f6g9v
- Google Maps. My Maps. (n.d.). Retrieved from <https://www.google.co.uk/maps/about/mymaps/>
- Gore, M. A., Rowat, D., Hall, J., Gell, F. R., & Ormond, R. F. (2008). Transatlantic migration and deep mid-ocean diving by basking shark. *Biology letters*, 4(4), 395-398. DOI: doi.org/10.1098/rsbl.2008.0147
- Grieves, R. M., & Jeffery, K. J. (2017). The representation of space in the brain. *Behavioural processes*, 135, 113-131. DOI: doi.org/10.1016/j.beproc.2016.12.012
- Grison, E., Gyselinck, V., Burkhardt, J. M., & Wiener, J. M. (2017). [Route planning with transportation network maps: an eye-tracking study](#). *Psychological research*, 81(5), 1020-1034. DOI:
- Hafting, T., Fyhn, M., Molden, S., Moser, M. B., & Moser, E. I. (2005). Microstructure of a spatial map in the entorhinal cortex. *Nature*, 436(7052), 801-806. DOI: doi.org/10.1038/nature03721

- Hansen, L. P., Jonsson, N., & Jonsson, B. (1993). Oceanic migration in homing Atlantic salmon. *Animal behaviour*, 45(5), 927-941. DOI: doi.org/10.1006/anbe.1993.1112
- Hartmeyer, S., Grzeschik, R., Wolbers, T., & Wiener, J. M. (2017). The effects of attentional engagement on route learning performance in a virtual environment: An aging study. *Frontiers in aging neuroscience*, 9, 235. DOI: doi.org/10.3389/fnagi.2017.00235
- Hejtmánek, L., Oravcová, I., Motýl, J., Horáček, J., & Fajnerová, I. (2018). Spatial knowledge impairment after GPS guided navigation: Eye-tracking study in a virtual town. *International Journal of Human-Computer Studies*, 116, 15-24. DOI: doi.org/10.1016/j.ijhcs.2018.04.006
- Hillier, B. (2007). *Space is the machine: a configurational theory of architecture*. Space Syntax. ISBN-13: [9780955622403](https://doi.org/10.1016/j.ijhcs.2018.04.006)
- Hillier, B., & Hanson, J. (1989). *The social logic of space*. Cambridge university press.
- Hillier, B., Penn, A., Hanson, J., Grajewski, T., & Xu, J. (1993). Natural movement: or, configuration and attraction in urban pedestrian movement. *Environment and Planning B: planning and design*, 20(1), 29-66. DOI: doi.org/10.1068/b200029
- Hölscher, C., Büchner, S. J., Meilinger, T., & Strube, G. (2009). Adaptivity of wayfinding strategies in a multi-building ensemble: The effects of spatial structure, task requirements, and metric information. *Journal of Environmental Psychology*, 29(2), 208-219. DOI: doi.org/10.1016/j.jenvp.2008.05.010
- Hölscher, C., Meilinger, T., Vrachliotis, G., Brösamle, M., & Knauff, M. (2006). Up the down staircase: Wayfinding strategies in multi-level buildings. *Journal of Environmental Psychology*, 26(4), 284-299. DOI: doi.org/10.1016/j.jenvp.2006.09.002
- Hölscher, C., Tenbrink, T., & Wiener, J. M. (2011). Would you follow your own route description? Cognitive strategies in urban route planning. *Cognition*, 121(2), 228-247. DOI: doi.org/10.1016/j.cognition.2011.06.005
- Hommel, B., Gehrke, J., & Knuf, L. (2000). Hierarchical coding in the perception and memory of spatial layouts. *Psychological research*, 64(1), 1-10. DOI: doi.org/10.1007/s004260000032
- Howard Jr, J. H., Howard, D. V., Dennis, N. A., Yankovich, H., & Vaidya, C. J. (2004). Implicit spatial contextual learning in healthy aging. *Neuropsychology*, 18(1), 124. DOI: doi.org/10.1037/0894-4105.18.1.124
- Howard, M. W., Fotedar, M. S., Datey, A. V., & Hasselmo, M. E. (2005). The temporal context model in spatial navigation and relational learning: toward a common

- explanation of medial temporal lobe function across domains. *Psychological review*, 112(1), 75. DOI: doi.org/10.1037/0033-295X.112.1.75
- Hurts, K. (2005, September). Common region and spatial performance using map-like displays. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 49, No. 17, pp. 1593-1597). Sage CA: Los Angeles, CA: Sage Publications. DOI: doi.org/10.1177/154193120504901720
- Hutcheson, A. T., & Wedell, D. H. (2009). Moderating the route angularity effect in a virtual environment: Support for a dual memory representation. *Memory & cognition*, 37(4), 514-521. DOI: doi.org/10.3758/MC.37.4.514
- Huys, Q. J., Eshel, N., O'Nions, E., Sheridan, L., Dayan, P., & Roiser, J. P. (2012). Bonsai trees in your head: how the pavlovian system sculpts goal-directed choices by pruning decision trees. *PLoS Comput Biol*, 8(3), e1002410. DOI: doi.org/10.1371/journal.pcbi.1002410
- Ishikawa, T., & Kiyomoto, M. (2008, September). Turn to the left or to the west: verbal navigational directions in relative and absolute frames of reference. In *International Conference on Geographic Information Science* (pp. 119-132). Springer, Berlin, Heidelberg. DOI: doi.org/10.1007/978-3-540-87473-7_8
- Ishikawa, T., Fujiwara, H., Imai, O., & Okabe, A. (2008). Wayfinding with a GPS-based mobile navigation system: A comparison with maps and direct experience. *Journal of environmental psychology*, 28(1), 74-82. DOI: doi.org/10.1016/j.jenvp.2007.09.002
- Jacobs, J., Weidemann, C. T., Miller, J. F., Solway, A., Burke, J. F., Wei, X. X., Suthana, N., Sperling, M. R., Sharan, A. D., Fried, I. & Kahana, M. J. (2013). Direct recordings of grid-like neuronal activity in human spatial navigation. *Nature neuroscience*, 16(9), 1188-1190. DOI: doi.org/10.1038/nn.3466
- Jafarpour, A., & Spiers, H. (2017). Familiarity expands space and contracts time. *Hippocampus*, 27(1), 12-16. DOI: doi.org/10.1002/hipo.22672
- Janson, C. H., & Goldsmith, M. L. (1995). Predicting group size in primates: foraging costs and predation risks. *Behavioral Ecology*, 6(3), 326-336. DOI: doi.org/10.1093/beheco/6.3.326
- Javadi, A. H., Emo, B., Howard, L. R., Zisch, F. E., Yu, Y., Knight, R., Silva, P. S. & Spiers, H. J. (2017). Hippocampal and prefrontal processing of network topology to simulate the future. *Nature communications*, 8(1), 1-11. DOI: doi.org/10.1038/ncomms14652

- Jiang, B., & Claramunt, C. (2004). Topological analysis of urban street networks. *Environment and Planning B: Planning and design*, 31(1), 151-162. DOI: doi.org/10.1068/b306
- Johnson, C. W., Shea, C., & Holloway, C. M. (2008). The role of trust and interaction in GPS related accidents: a human factors safety assessment of the global positioning system (GPS). Retrieved from https://eprints.gla.ac.uk/40172/1/Johnson_Shea_Holloway_GPS.pdf
- June 1654: An Ordinance for the Regulation of Hackney-Coachmen in London and the places adjacent.', in *Acts and Ordinances of the Interregnum, 1642-1660*, ed. C H Firth and R S Rait (London, 1911), pp. 922-924. *British History Online*. Retrieved from <http://www.british-history.ac.uk/no-series/acts-ordinances-interregnum/pp922-924>
- Key: highway. (2020, May 1). Retrieved from <https://wiki.openstreetmap.org/wiki/Key:highway>
- Klippel, A., Knuf, L., Hommel, B., & Freksa, C. (2004, October). Perceptually induced distortions in cognitive maps. In *International Conference on Spatial Cognition* (pp. 204-213). Springer, Berlin, Heidelberg. DOI: doi.org/10.1007/978-3-540-32255-9_12
- Knoblock, C. A. (1990). Abstracting the tower of hanoi. In *Working Notes of AAAI-90 Workshop on Automatic Generation of Approximations and Abstractions* (pp. 13-23). Boston, MA: Citeseer. DOI: doi.org/10.1007/978-1-4613-1523-0_5
- Koch, A. L., Carr, A., & Ehrenfeld, D. W. (1969). The problem of open-sea navigation: the migration of the green turtle to Ascension Island. *Journal of Theoretical Biology*, 22(1), 163-179. DOI: [doi.org/10.1016/0022-5193\(69\)90085-X](https://doi.org/10.1016/0022-5193(69)90085-X)
- König, S. U., Schumann, F., Keyser, J., Goeke, C., Krause, C., Wache, S., Lytochkin, A., Ebert, M., Brunsch, V., Wahn, B., Kaspar, K., Nagel, S. K., Meilinger, T., Buelthoff, H., Wolbers, T., Buechel, C., & Koenig, P. (2016). Learning new sensorimotor contingencies: Effects of long-term use of sensory augmentation on the brain and conscious perception. *PLoS One*, 11(12), e0166647. DOI: doi.org/10.1371/journal.pone.0166647
- Kosslyn, S. M., Pinker, S., Smith, G. E., & Shwartz, S. P. (1979). On the demystification of mental imagery. *Behavioral and Brain Sciences*, 2(4), 535-548. DOI: doi.org/10.1017/S0140525X00064268
- Kuipers, B., Tecuci, D. G., & Stankiewicz, B. J. (2003). The skeleton in the cognitive map: A computational and empirical exploration. *Environment and behavior*, 35(1), 81-106. DOI: doi.org/10.1177/0013916502238866

- Kunz, L., Schroder, T. N., Lee, H., Montag, C., Lachmann, B., Sariyska, R., Reuter, M., Stirnberg, R., Stocker, T., Messing-Floeter, P.C., Fell, J., Doeller, C.F., & Axmacher, N. (2015). Reduced grid-cell-like representations in adults at genetic risk for Alzheimer's disease. *Science*, 350(6259), 430–433. DOI: doi.org/10.1126/science.aac8128
- Las, L., & Ulanovsky, N. (2014). Hippocampal neurophysiology across species. In *Space, time and memory in the hippocampal formation* (pp. 431-461). Springer, Vienna. DOI: doi.org/10.1007/978-3-7091-1292-2_16
- Layers of London. (2020). Retrieved from <https://www.layersoflondon.org/>
- Learn the Knowledge of London, Transport for London. (n.d.). Retrieved from <https://tfl.gov.uk/info-for/taxis-and-private-hire/licensing/learn-the-knowledge-of-london>
- Lloyd, R. (2013). The estimation of distance and direction from cognitive maps. *The American Cartographer*, 16(2), 109-122. DOI: doi.org/10.1559/152304089783875415
- London Metropolitan Archives (2013, June). Retrieved from <https://www.cityoflondon.gov.uk/things-to-do/london-metropolitan-archives/visitor-information/Documents/46-vehicle-registration-and-licensing-records.pdf>
- London's Roman Roads. (2013, February 25). Retrieved from <https://mappinglondon.co.uk/2013/londons-roman-roads/>
- Lordan, R. (2018). [The Knowledge: Train Your Brain Like A Cabbie](#). Quercus.
- Lövdén, M., Schaefer, S., Noack, H., Bodammer, N. C., Kühn, S., Heinze, H. J., Düzel, E., Bäckman, L. & Lindenberger, U. (2012). Spatial navigation training protects the hippocampus against age-related changes during early and late adulthood. *Neurobiology of aging*, 33(3), 620-e9. DOI: doi.org/10.1016/j.neurobiolaging.2011.02.013
- Luschi, P., Papi, F., Liew, H. C., Chan, E. H., & Bonadonna, F. (1996). Long-distance migration and homing after displacement in the green turtle (*Chelonia mydas*): a satellite tracking study. *Journal of Comparative Physiology A*, 178(4), 447-452. DOI: doi.org/10.1007/BF00190175
- Lynch, K. (1960). [The image of the city](#) (Vol. 11). MIT press.
- Maguire, E. A., Frackowiak, R. S., & Frith, C. D. (1997). Recalling routes around London: activation of the right hippocampus in taxi drivers. *Journal of neuroscience*, 17(18), 7103-7110. DOI: doi.org/10.1523/JNEUROSCI
- Maguire, E. A., Gadian, D. G., Johnsrude, I. S., Good, C. D., Ashburner, J., Frackowiak, R. S., & Frith, C. D. (2000). Navigation-related structural change in the hippocampi of taxi

- drivers. *Proceedings of the National Academy of Sciences*, 97(8), 4398-4403. DOI: doi.org/10.1073/pnas.070039597
- Maguire, E. A., Nannery, R., & Spiers, H. J. (2006). Navigation around London by a taxi driver with bilateral hippocampal lesions. *Brain*, 129(11), 2894-2907. DOI: doi.org/10.1093/brain/awl286
- Maguire, E. A., Spiers, H. J., Good, C. D., Hartley, T., Frackowiak, R. S., & Burgess, N. (2003). Navigation expertise and the human hippocampus: a structural brain imaging analysis. *Hippocampus*, 13(2), 250-259. DOI: doi.org/10.1002/hipo.10087
- Maguire, E. A., Woollett, K., & Spiers, H. J. (2006). London taxi drivers and bus drivers: a structural MRI and neuropsychological analysis. *Hippocampus*, 16(12), 1091-1101. DOI: doi.org/10.1002/hipo.20233
- Manley, E. (2014). Identifying functional urban regions within traffic flow. *Regional Studies, Regional Science*, 1(1), 40-42. DOI: doi.org/10.1080/21681376.2014.891649
- Manley, E. J., Orr, S. W., & Cheng, T. (2015). A heuristic model of bounded route choice in urban areas. *Transportation Research Part C: Emerging Technologies*, 56, 195-209. DOI: doi.org/10.1016/j.trc.2015.03.020
- Mapbox. (2020). Retrieved from <https://www.mapbox.com/>
- Marchette, S. A., Vass, L. K., Ryan, J., & Epstein, R. A. (2014). Anchoring the neural compass: coding of local spatial reference frames in human medial parietal lobe. *Nature neuroscience*, 17(11), 1598. DOI: doi.org/10.1038/nn.3834
- Masucci, A. P., Arcaute, E., Hatna, E., Stanilov, K., & Batty, M. (2015). On the problem of boundaries and scaling for urban street networks. *Journal of the Royal Society Interface*, 12(111), 20150763. DOI: doi.org/10.1098/rsif.2015.0763
- Masucci, A. P., Smith, D., Crooks, A., & Batty, M. (2009). Random planar graphs and the London street network. *The European Physical Journal B*, 71(2), 259-271. DOI: doi.org/10.1140/epjb/e2009-00290-4
- McKinlay, R. (2016). Technology: Use or lose our navigation skills. *Nature*, 531(7596), 573-575. DOI: doi.org/10.1038/531573a
- McNamara, T. P. (1986). Mental representations of spatial relations. *Cognitive psychology*, 18(1), 87-121. DOI: [doi.org/10.1016/0010-0285\(86\)90016-2](https://doi.org/10.1016/0010-0285(86)90016-2)
- McNamee, D., Wolpert, D. M., & Lengyel, M. (2016). [Efficient state-space modularization for planning: theory, behavioral and neural signatures](#). In *Advances in neural information processing systems* (pp. 4511-4519).

- Meilinger, T., Frankenstein, J., & Bühlhoff, H. H. (2014). When in doubt follow your nose—a wayfinding strategy. *Frontiers in psychology*, 5, 1363. DOI: doi.org/10.3389/fpsyg.2014.01363
- Meilinger, T., Hölscher, C., Buchner, S. J., & Brosamle, M. (2007). How much information do you need? Schematic maps in wayfinding and self localisation. In T. Barkowsky (Ed.), *Spatial cognition V—reasoning, action, interaction* (pp. 381–400). Berlin: Springer. DOI:doi.org/10.1007/978-3-540-75666-8_22.
- Meilinger, T., Knauff, M., & Bühlhoff, H. H. (2008). Working memory in wayfinding—A dual task experiment in a virtual city. *Cognitive Science*, 32(4), 755-770. DOI: doi.org/10.1080/03640210802067004
- Meilinger, T., Riecke, B. E., & Bühlhoff, H. H. (2014). Local and global reference frames for environmental spaces. *The Quarterly Journal of Experimental Psychology*, 67(3), 542-569. DOI: doi.org/10.1080/17470218.2013.821145
- Menzel, R., Geiger, K., Chittka, L., Joerges, J., Kunze, J., & Müller, U. (1996). [The knowledge base of bee navigation](#). *Journal of Experimental Biology*, 199(1), 141-146.
- Milford, M., & Wyeth, G. (2007, September). Spatial mapping and map exploitation: a bio-inspired engineering perspective. In *International Conference on Spatial Information Theory* (pp. 203-221). Springer, Berlin, Heidelberg. DOI: doi.org/10.1007/978-3-540-74788-8_13
- Miller, K. J., & Venditto, S. J. C. (2020). Multi-step Planning in the Brain. *Current Opinion in Behavioral Sciences*, 38, 29-39. DOI: doi.org/10.1016/j.cobeha.2020.07.003
- Milne, G. (1995). *English Heritage: Roman London*. London, UK: Batsford.
- Moffat, S. D., Hampson, E., & Hatzipantelis, M. (1998). Navigation in a “virtual” maze: Sex differences and correlation with psychometric measures of spatial ability in humans. *Evolution and Human Behavior*, 19(2), 73-87. DOI: [doi.org/10.1016/S1090-5138\(97\)00104-9](https://doi.org/10.1016/S1090-5138(97)00104-9)
- Montello, D. R. (2002). Cognitive map-design research in the twentieth century: Theoretical and empirical approaches. *Cartography and Geographic Information Science*, 29(3), 283-304. DOI: doi.org/10.1559/152304002782008503
- Montello, D. R. (2010). You are where? The function and frustration of you-are-here (YAH) maps. *Spatial Cognition & Computation*, 10(2-3), 94-104. DOI: doi.org/10.1080/13875860903585323
- Montello, D. R., Grossner, K., & Janelle, D. G. (2014). [Concepts for spatial learning and education: An introduction](#). In D. R. Montello, K. E. Grossner, & D. G. Janelle (Eds.),

- Space in mind: Concepts for spatial learning and education* (pp. 3-29). Cambridge, MA: MIT Press.
- Montello, D. R., Lovelace, K. L., Golledge, R. G., & Self, C. M. (1999). Sex-related differences and similarities in geographic and environmental spatial abilities. *Annals of the Association of American geographers*, 89(3), 515-534. DOI: doi.org/10.1111/0004-5608.00160
- Morris, R. G., Garrud, P., Rawlins, J. A., & O'Keefe, J. (1982). Place navigation impaired in rats with hippocampal lesions. *Nature*, 297(5868), 681-683. DOI: doi.org/10.1038/297681a0
- Münzer, S., Zimmer, H. D., & Baus, J. (2012). Navigation assistance: A trade-off between wayfinding support and configural learning support. *Journal of experimental psychology: applied*, 18(1), 18. DOI: doi.org/10.1037/a0026553
- Münzer, S., Zimmer, H. D., Schwalm, M., Baus, J., & Aslan, I. (2006). Computer-assisted navigation and the acquisition of route and survey knowledge. *Journal of environmental psychology*, 26(4), 300-308. DOI: doi.org/10.1037/a0026553
- Newman, E. L., Caplan, J. B., Kirschen, M. P., Korolev, I. O., Sekuler, R., & Kahana, M. J. (2007). Learning your way around town: How virtual taxicab drivers learn to use both layout and landmark information. *Cognition*, 104(2), 231-253. DOI: doi.org/10.1016/j.cognition.2006.05.013
- Newton, R. (1857). *The Omnibuses of London*. In Urban, S., *The Gentleman's Magazine and Historical Review* (pp 663-664). Vol 203.
- Nicholas, D. M. (2014). *The growth of the medieval city: from late antiquity to the early fourteenth century*. Routledge.
- Nichols, W. J., Resendiz, A., Seminoff, J. A., & Resendiz, B. (2000). [Transpacific migration of a loggerhead turtle monitored by satellite telemetry](#). *Bulletin of Marine Science*, 67(3), 937-947.
- Norris, R. P., & Harney, B. Y. (2014). Songlines and navigation in Wardaman and other Australian Aboriginal cultures. arXiv preprint arXiv:1404.2361. arXiv: [1404.2361](https://arxiv.org/abs/1404.2361)
- O'Doherty, J. P., Lee, S. W., & McNamee, D. (2015). The structure of reinforcement-learning mechanisms in the human brain. *Current Opinion in Behavioral Sciences*, 1, 94-100. DOI: doi.org/10.1016/j.cobeha.2014.10.004
- Oftedal, O. T. (1991). The nutritional consequences of foraging in primates: the relationship of nutrient intakes to nutrient requirements. *Philosophical Transactions of*

- the Royal Society of London. Series B: Biological Sciences, 334(1270), 161-170. DOI: doi.org/10.1098/rstb.1991.0105
- Okabayashi, H., & Glynn, S. M. (1984). Spatial cognition: systematic distortions in cognitive maps. *The Journal of General Psychology*, 111(2), 271-279. DOI: doi.org/10.1080/00221309.1984.9921116
- O'Keefe, J., & Conway, D. H. (1978). Hippocampal place units in the freely moving rat: why they fire where they fire. *Experimental brain research*, 31(4), 573-590. DOI: doi.org/10.1007/BF00239813
- O'Keefe, J., & Dostrovsky, J. (1971). The hippocampus as a spatial map: Preliminary evidence from unit activity in the freely-moving rat. *Brain research*. DOI: [doi.org/10.1016/0006-8993\(71\)90358-1](https://doi.org/10.1016/0006-8993(71)90358-1)
- O'keefe, J., & Nadel, L. (1978). *The hippocampus as a cognitive map*. Oxford: Clarendon Press. ISBN: [0-19-857206-9](https://www.isbn-international.org/product/0-19-857206-9)
- Open Geography Portal. (2020). Retrieved from <https://geoportal.statistics.gov.uk/>
- OpenStreetMaps (n.d.). Retrieved from <https://www.openstreetmap.org/about>
- OS MasterMap Integrated Transport Network (ITN) Layer. Coverage: London, October 2018. Ordnance Survey, GB. Using: EDINA Digimap Ordnance Survey Service, Retrieved from <https://digimap.edina.ac.uk/>
- Oxford Learner's Dictionary. (n.d.). Navigation. Retrieved November 03, 2020, from <https://www.oxfordlearnersdictionaries.com/definition/english/navigation>
- Packard, M. G., Hirsh, R., & White, N. M. (1989). Differential effects of fornix and caudate nucleus lesions on two radial maze tasks: evidence for multiple memory systems. *Journal of Neuroscience*, 9(5), 1465-1472. DOI: doi.org/10.1523/JNEUROSCI.09-05-01465.1989
- Pailhous J. (1970). *La représentation de l'espace urbain: l'exemple du chauffeur de taxi*. Paris: Presses Universitaires de France.
- Pailhous, J. (1969). [Représentation de l'espace urbain et cheminements](#). *Le travail humain*, 87-139.
- Pailhous, J. (1984). The representation of urban space: its development and its role in the organisation of journeys. *Social representations*, 311-327.
- Peruch, P., Girardo, M. D., & Garling, T. (1989). Distance cognition by taxi drivers and the general public. *Journal of Environmental Psychology*, 9(3), 233-239. DOI: [doi.org/10.1016/S0272-4944\(89\)80037-4](https://doi.org/10.1016/S0272-4944(89)80037-4)

- Pezzulo, G., Rigoli, F., & Friston, K. J. (2018). Hierarchical active inference: A theory of motivated control. *Trends in cognitive sciences*, 22(4), 294-306. DOI: doi.org/10.1016/j.tics.2018.01.009
- Préfecture de Police, Démarches & Services. Vous souhaitez devenir conducteur de taxi. (2020). Retrieved from <https://www.prefecturedepolice.interieur.gouv.fr/Demarches/Professionnel/Transports/Taxis-parisiens/Vous-souhaitez-devenir-conducteur-de-taxi>
- Reppert, S. M., Gegear, R. J., & Merlin, C. (2010). Navigational mechanisms of migrating monarch butterflies. *Trends in neurosciences*, 33(9), 399-406. DOI: doi.org/10.1016/j.tins.2010.04.004
- Robinson, A. T. (2020). *The impact of spatial boundaries on wayfinding and landmark memory: a developmental perspective* (Doctoral dissertation, University of Alabama Libraries).
- S. Milgram. (1976). [Psychological maps of Paris](#). In H.M. Proshansky, W.H. Ittelson, L.G. Rivlin (Eds.), *Environmental psychology: People and their physical settings* (2nd ed.), Rinehart & Winston, New York (1976), pp. 88-113
- Sadalla, E. K., & Magel, S. G. (1980). The perception of traversed distance. *Environment and Behavior*, 12(1), 65-79. DOI: doi.org/10.1177/0013916580121005
- Sadalla, E. K., & Staplin, L. J. (1980). The perception of traversed distance: Intersections. *Environment and Behavior*, 12(2), 167-182. DOI: doi.org/10.1177/0013916580122003
- Salthouse, T. A., Babcock, R. L., Skovronek, E., Mitchell, D. R., & Palmon, R. (1990). Age and experience effects in spatial visualization. *Developmental Psychology*, 26(1), 128. DOI: doi.org/10.1037/0012-1649.26.1.128
- Schick, W. (2018). [Acquisition and consolidation of hierarchical representations of space](#) (Doctoral dissertation, Eberhard-Karls-Universität Tübingen).
- Schick, W., Halfmann, M., Hardiess, G., Hamm, F., & Mallot, H. A. (2019). Language cues in the formation of hierarchical representations of space. *Spatial Cognition & Computation*, 19(3), 252-281. DOI: doi.org/10.1080/13875868.2019.1576692
- Shapiro, M. (2015). A limited positioning system for memory. *Hippocampus*, 25(6), 690-696. DOI: doi.org/10.1002/hipo.22448
- Shine, J. P., Valdés-Herrera, J. P., Hegarty, M., & Wolbers, T. (2016). The human retrosplenial cortex and thalamus code head direction in a global reference frame. *Journal of Neuroscience*, 36(24), 6371-6381. DOI: doi.org/10.1523/JNEUROSCI.1268-15.2016

- Siegel, A. W., & White, S. H. (1975). The development of spatial representations of large-scale environments. In *Advances in child development and behavior* (Vol. 10, pp. 9-55). JAI. DOI: [doi.org/10.1016/S0065-2407\(08\)60007-5](https://doi.org/10.1016/S0065-2407(08)60007-5)
- Simms, A. (1979). Medieval Dublin: a topographical analysis. *Irish Geography*, 12(1), 25-41. DOI: doi.org/10.1080/00750777909555741
- Skok, W. (1999). Knowledge management: London taxi cabs case study. In *Proceedings of the 1999 ACM SIGCPR conference on Computer personnel research* (pp. 94-101). DOI: doi.org/10.1145/299513.299625
- Skok, W. (2004). Knowledge management: Taxis Parisiens case study. *Knowledge Management Research & Practice*, 2(3), 147-154. DOI: doi.org/10.1057/palgrave.kmrp.8500035
- Skok, W., & Martinez, J. A. (2010). An international taxi cab evaluation: comparing Madrid with London, New York, and Paris. *Knowledge and Process Management*, 17(3), 145-153. DOI: doi.org/10.1002/kpm.346
- Smith, K. (2011). 'The Knowledge' enlarges your brain. *Nature News*. DOI: doi.org/10.1038/nature.2011.9602
- Solway, A., Diuk, C., Córdova, N., Yee, D., Barto, A. G., Niv, Y., & Botvinick, M. M. (2014). Optimal behavioral hierarchy. *PLOS Comput Biol*, 10(8), e1003779. DOI: doi.org/10.1371/journal.pcbi.1003779
- Sorby, S. A. (2009). [Developing 3-D spatial visualization skills](#). *Engineering Design Graphics Journal*, 63(2).
- Spiers, H. J., & Maguire, E. A. (2006). Thoughts, behaviour, and brain dynamics during navigation in the real world. *Neuroimage*, 31(4), 1826-1840. DOI: doi.org/10.1016/j.neuroimage.2006.01.037
- Spiers, H. J., & Maguire, E. A. (2008). The dynamic nature of cognition during wayfinding. *Journal of environmental psychology*, 28(3), 232-249. DOI: doi.org/10.1016/j.jenvp.2008.02.006
- Spriggs, M. J., Kirk, I. J., & Skelton, R. W. (2018). Hex Maze: A new virtual maze able to track acquisition and usage of three navigation strategies. *Behavioural brain research*, 339, 195-206. DOI: doi.org/10.1016/j.bbr.2017.11.041
- Squire, L. R., & Zola, S. M. (1996). Structure and function of declarative and nondeclarative memory systems. *Proceedings of the National Academy of Sciences*, 93(24), 13515-13522. DOI: doi.org/10.1073/pnas.93.24.13515

- Stansfeld, K. (2019). *Mapping multiplicity: place, difference and conviviality in Finsbury Park, London* (Doctoral dissertation, Royal Holloway, University of London).
- Stevens, A., & Coupe, P. (1978). Distortions in judged spatial relations. *Cognitive psychology*, 10(4), 422-437. DOI: [doi.org/10.1016/0010-0285\(78\)90006-3](https://doi.org/10.1016/0010-0285(78)90006-3)
- Streeter, L. A., & Vitello, D. (1986). A profile of drivers' map-reading abilities. *Human factors*, 28(2), 223-239. DOI: doi.org/10.1177/001872088602800210
- Tatton-Brown, T. (1986). The topography of Anglo-Saxon London. *Antiquity*, 60(228), 21-28. DOI: doi.org/10.1017/S0003598X00057586
- Taube, J. S. (1995). Head direction cells recorded in the anterior thalamic nuclei of freely moving rats. *Journal of Neuroscience*, 15(1), 70-86. DOI: doi.org/10.1523/JNEUROSCI.15-01-00070.1995
- Taube, J. S., Muller, R. U., & Ranck, J. B. (1990). Head-direction cells recorded from the postsubiculum in freely moving rats. I. Description and quantitative analysis. *Journal of Neuroscience*, 10(2), 420-435. DOI: doi.org/10.1523/JNEUROSCI.10-02-00420.1990
- The Knowledge, London's Legendary Taxi-Driver Test Puts Up a Fight in the Age of GPS (2014, November 10). Retrieved from <https://www.nytimes.com/2014/11/10/t-magazine/london-taxi-test-knowledge.html>
- The London Taxi Experience - The Knowledge. (2020). Retrieved from http://www.the-london-taxi.com/london_taxi_knowledge
- Thorndyke, P. W. (1981). Distance estimation from cognitive maps. *Cognitive psychology*, 13(4), 526-550. DOI: [doi.org/10.1016/0010-0285\(81\)90019-0](https://doi.org/10.1016/0010-0285(81)90019-0)
- Thorpe, J. E. (1988). [Salmon migration](#). *Science Progress (1933-)*, 345-370.
- Toledo, S., Shohami, D., Schiffner, I., Lourie, E., Orchan, Y., Bartan, Y., & Nathan, R. (2020). Cognitive map-based navigation in wild bats revealed by a new high-throughput tracking system. *Science*, 369(6500), 188-193. DOI: doi.org/10.1126/science.aax6904
- Tolman, E. C. (1948). Cognitive maps in rats and men. *Psychological review*, 55(4), 189-208. DOI: doi.org/10.1037/h0061626
- Tomov, M. S., Yagati, S., Kumar, A., Yang, W., & Gershman, S. J. (2020). Discovery of hierarchical representations for efficient planning. *PLoS computational biology*, 16(4), e1007594. DOI: doi.org/10.1371/journal.pcbi.1007594
- Tversky, B. (1981). Distortions in memory for maps. *Cognitive Psychology*, 13(3), 407-433. DOI: [doi.org/10.1016/0010-0285\(81\)90016-5](https://doi.org/10.1016/0010-0285(81)90016-5)

- Tversky, B. (1992). Distortions in cognitive maps. *Geoforum*, 23(2), 131e138. DOI: [doi.org/10.1016/0016-7185\(92\)90011-R](https://doi.org/10.1016/0016-7185(92)90011-R).
- van der Ham, I. J., & Claessen, M. H. (2020). How age relates to spatial navigation performance: Functional and methodological considerations. *Ageing Research Reviews*, 58, 101020. DOI: doi.org/10.1016/j.arr.2020.101020
- Venigalla, M., Zhou, X., & Zhu, S. (2017). Psychology of route choice in familiar networks: Minimizing turns and embracing signals. *Journal of Urban Planning and Development*, 143(2), 04016030. DOI: [doi.org/10.1061/\(ASCE\)UP.1943-5444.0000364](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000364)
- Walcott, C. (1996). [Pigeon homing: observations, experiments and confusions](#). *Journal of Experimental Biology*, 199(1), 21-27.
- Wallraff, H. G., & Wallraff, H. G. (2005). *Avian navigation: pigeon homing as a paradigm*. Springer Science & Business Media. ISBN [978-3-540-26432-3](#)
- Ward, G., & Allport, A. (1997). Planning and problem solving using the five disc Tower of London task. *The Quarterly Journal of Experimental Psychology Section A*, 50(1), 49-78. DOI: doi.org/10.1080/713755681
- Warren, W. H., Rothman, D. B., Schnapp, B. H., & Ericson, J. D. (2017). Wormholes in virtual space: From cognitive maps to cognitive graphs. *Cognition*, 166, 152-163. DOI: doi.org/10.1016/j.cognition.2017.05.020
- Weng, K. C., Foley, D. G., Ganong, J. E., Perle, C., Shillinger, G. L., & Block, B. A. (2008). Migration of an upper trophic level predator, the salmon shark *Lamna ditropis*, between distant ecoregions. *Marine Ecology Progress Series*, 372, 253-264. DOI: doi.org/10.3354/meps07706
- Wiener, J. M., & Mallot, H. A. (2003). 'Fine-to-coarse' route planning and navigation in regionalized environments. *Spatial cognition and computation*, 3(4), 331-358. DOI: doi.org/10.1207/s15427633scc0304_5
- Wiener, J. M., Carroll, D., Moeller, S., Bibi, I., Ivanova, D., Allen, P., & Wolbers, T. (2019). A novel virtual-reality-based route-learning test suite: Assessing the effects of cognitive aging on navigation. *Behavior Research Methods*, 1-11. DOI: doi.org/10.3758/s13428-019-01264-8
- Wiener, J. M., de Condappa, O., Harris, M. A., & Wolbers, T. (2013). Maladaptive bias for extrahippocampal navigation strategies in aging humans. *Journal of Neuroscience*, 33(14), 6012-6017. DOI: doi.org/10.1523/JNEUROSCI.0717-12.2013

- Wiener, J. M., Ehbauer, N. N., & Mallot, H. A. (2009). Planning paths to multiple targets: memory involvement and planning heuristics in spatial problem solving. *Psychological Research PRPF*, 73(5), 644. DOI: doi.org/10.1007/s00426-008-0181-3
- Wiener, J. M., Kmecova, H., & de Condappa, O. (2012). Route repetition and route retracing: effects of cognitive aging. *Frontiers in Aging Neuroscience*, 4, 7. DOI: doi.org/10.3389/fnagi.2012.00007
- Wiener, J. M., Schnee, A., & Mallot, H. A. (2004). Use and interaction of navigation strategies in regionalized environments. *Journal of Environmental Psychology*, 24(4), 475-493. DOI: doi.org/10.1016/j.jenvp.2004.09.006
- Wilson, E. O. (1958). [The beginnings of nomadic and group-predatory behavior in the ponerine ants](#). *Evolution*, 24-31.
- Wilson, E. O. (1971). [The insect societies](#). *The insect societies*.
- Winocur, G., Moscovitch, M., Fogel, S., Rosenbaum, R. S., & Sekeres, M. (2005). Preserved spatial memory after hippocampal lesions: effects of extensive experience in a complex environment. *Nature neuroscience*, 8(3), 273-275. DOI: doi.org/10.1038/nn1401
- Winter, S., Duckham, M., Kulik, L., & Kuipers, B. (Eds.). (2007). *Spatial Information Theory: 8th International Conference, COSIT 2007, Melbourne, Australia, September 19-23, 2007, Proceedings* (Vol. 4736). Springer. DOI: doi.org/10.1007/978-3-319-49487-6_2
- Wolbers, T., & Hegarty, M. (2010). What determines our navigational abilities? *Trends in cognitive sciences*, 14(3), 138-146. DOI: doi.org/10.1016/j.tics.2010.01.001
- Woollett, K., & Maguire, E. A. (2009). Navigational expertise may compromise anterograde associative memory. *Neuropsychologia*, 47(4), 1088-1095. DOI: doi.org/10.1016/j.neuropsychologia.2008.12.036
- Woollett, K., & Maguire, E. A. (2011). Acquiring “the Knowledge” of London's layout drives structural brain changes. *Current biology*, 21(24), 2109-2114. DOI: doi.org/10.1016/j.cub.2011.11.018
- Woollett, K., & Maguire, E. A. (2012). Exploring anterograde associative memory in London taxi drivers. *Neuroreport*, 23(15), 885. DOI: doi.org/10.1097/WNR.0b013e328359317e
- Woollett, K., Spiers, H. J., & Maguire, E. A. (2009). Talent in the taxi: a model system for exploring expertise. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1522), 1407-1416. DOI: doi.org/10.1098/rstb.2008.0288

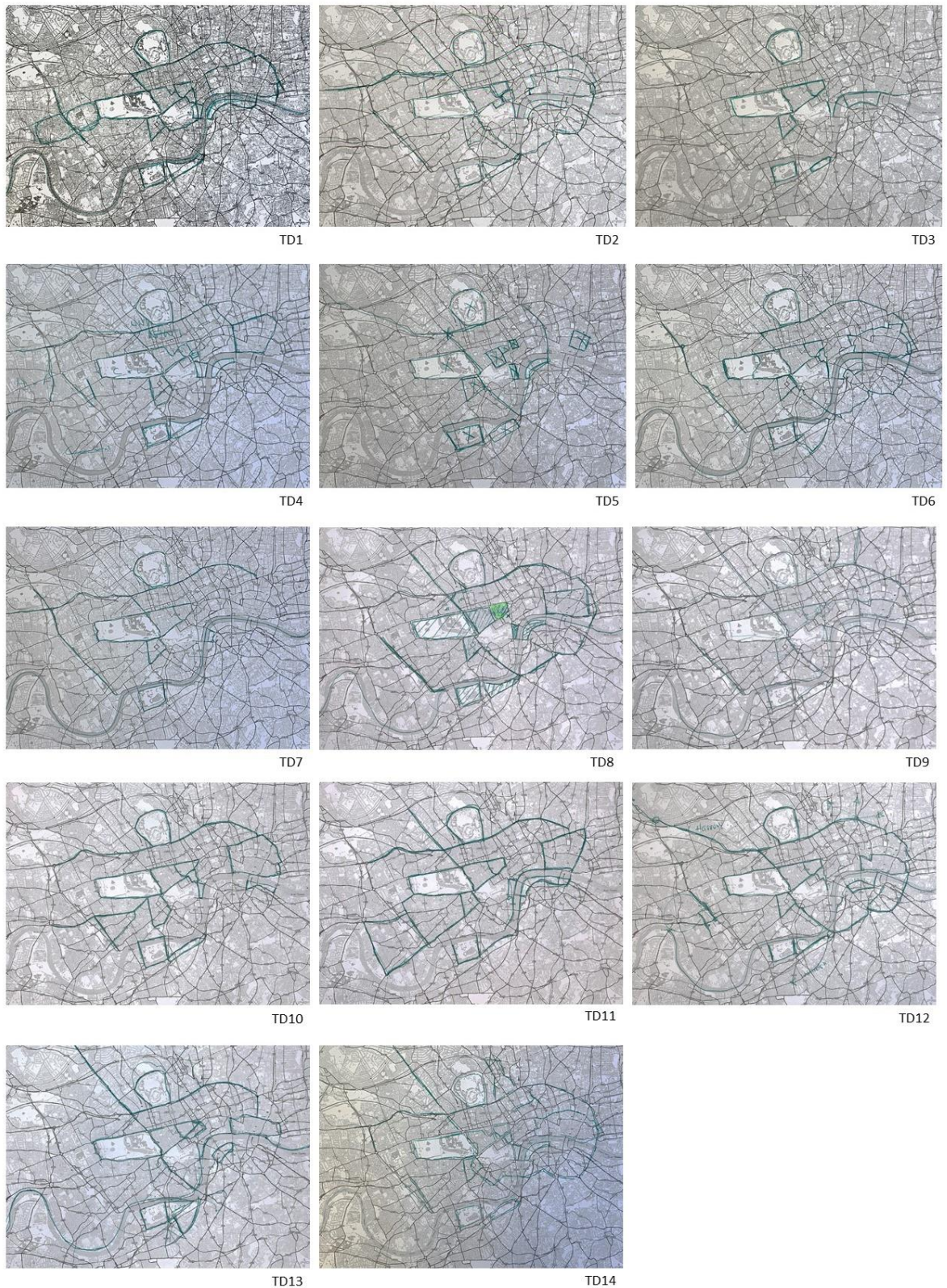
Working papers Series (2020, May). Retrieved from

https://www.ucl.ac.uk/bartlett/casa/sites/bartlett/files/casa_working_paper_222_2.pdf

Zhan, S., Merlin, C., Boore, J. L., & Reppert, S. M. (2011). The monarch butterfly genome yields insights into long-distance migration. *Cell*, *147*(5), 1171-1185. DOI:

doi.org/10.1016/j.cell.2011.09.052

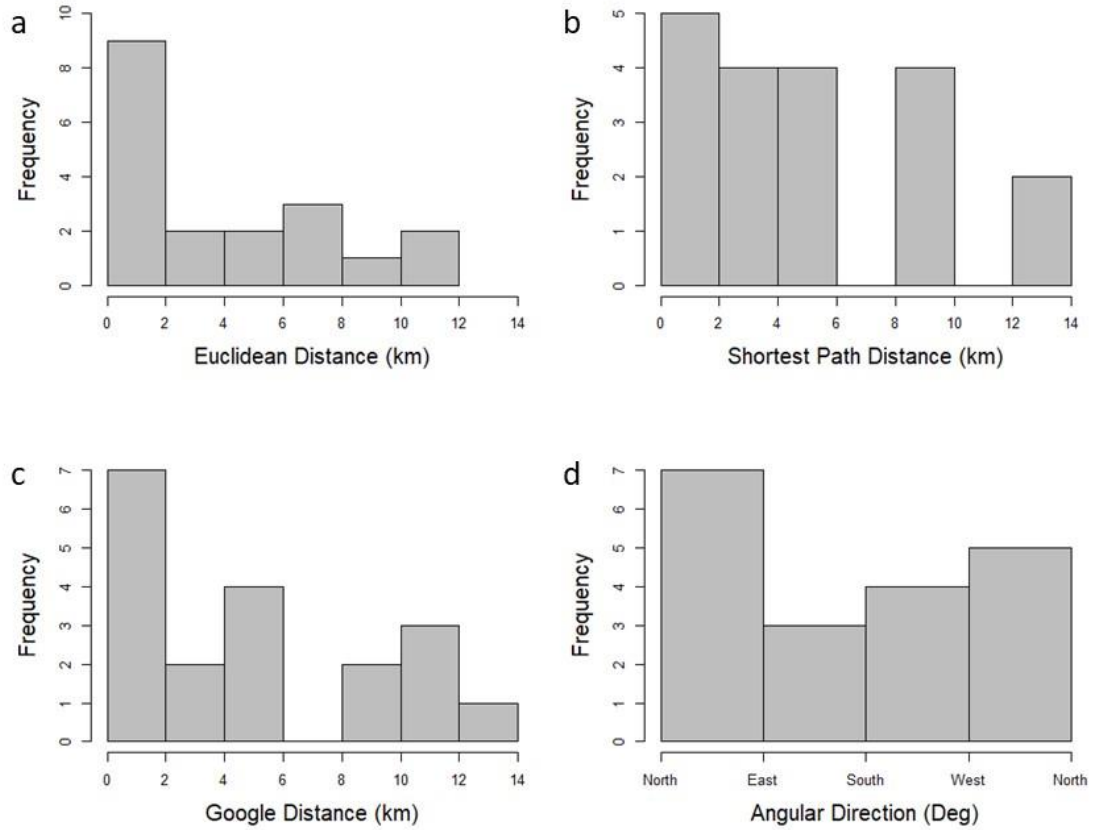
7. SUPPLEMENTARY MATERIAL FOR CHAPTER 3



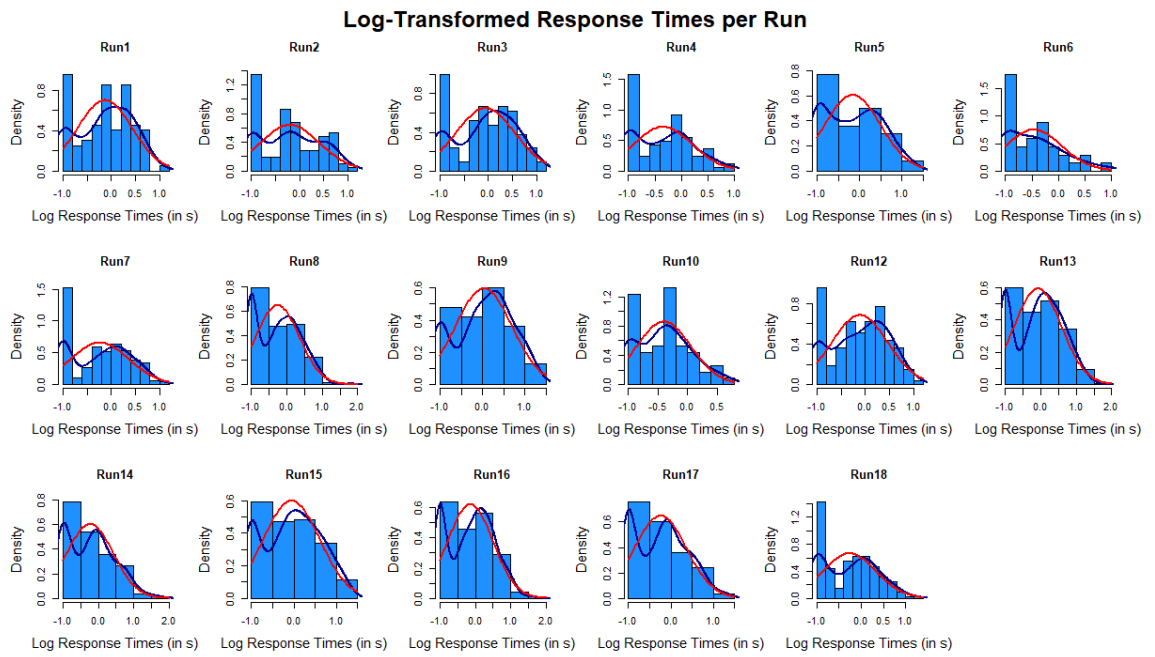
Supplementary Figure 3.1. Boundary drawings. London taxi drivers were asked to indicate the boundaries of several London districts and areas on a paper map. The data was collected from $N = 14$ taxi drivers and was later digitised. The drawing from one taxi driver, TD5, was excluded from the analysis, as this driver did not follow instructions to highlight streets and other spatial structures that would constitute boundaries. Instead, the driver marked the location through an 'X' and drew a box around the area unrelated to the street network, which was not precise enough for further analysis.

8. SUPPLEMENTARY MATERIAL FOR CHAPTER 4

Geographical Properties of Routes Tested

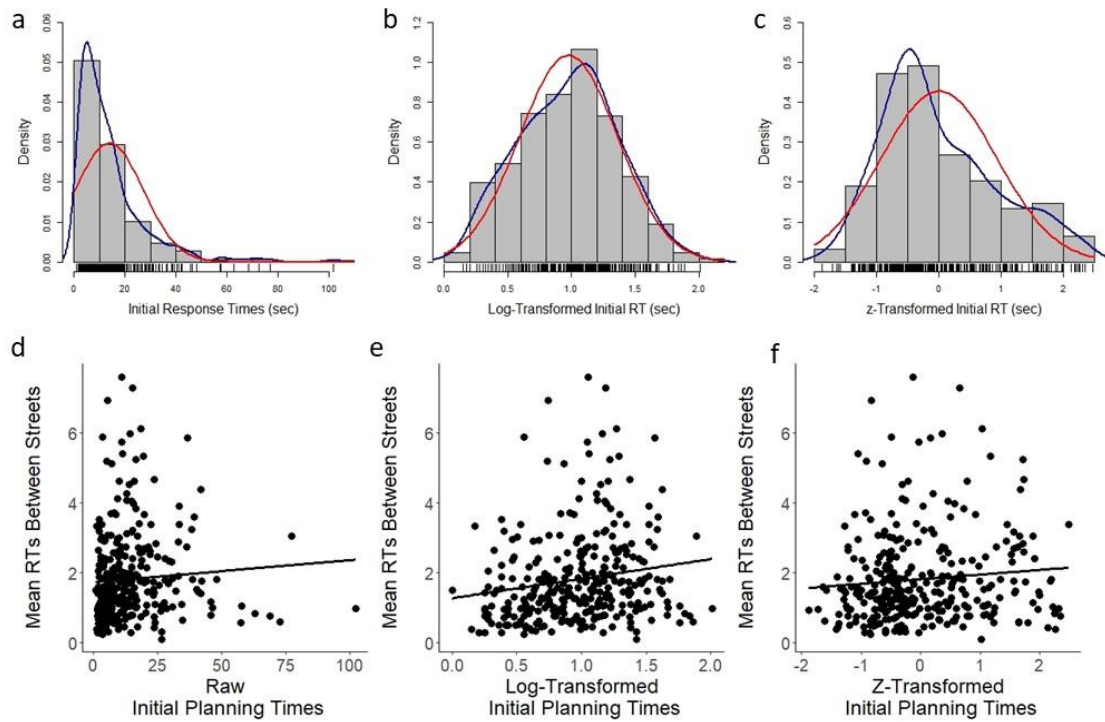


Supplementary Figure 8.1. Geographical properties of route planning tasks. The tasks that were selected for this study were counterbalanced based on different geographical properties (see also **Table 4.1**). These properties included the Euclidean distance from the origin to the destination (a), the shortest path distance for the origin-destination pair (b), the shortest distance Google Maps suggested for the task (c) and cardinal direction of the destination, viewed from the origin (d).

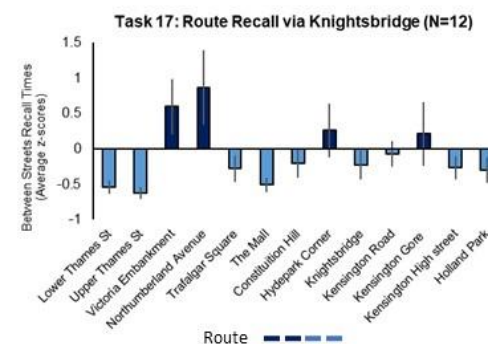
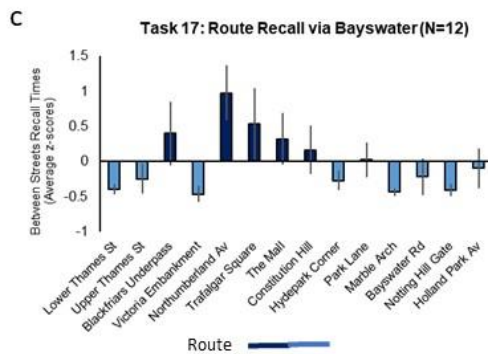
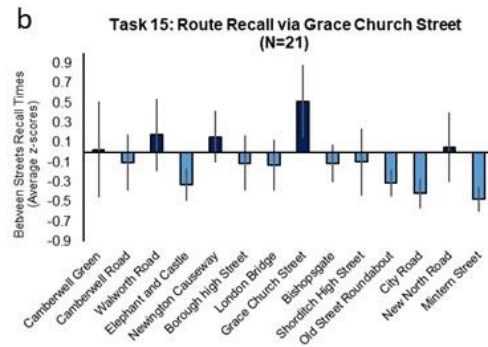
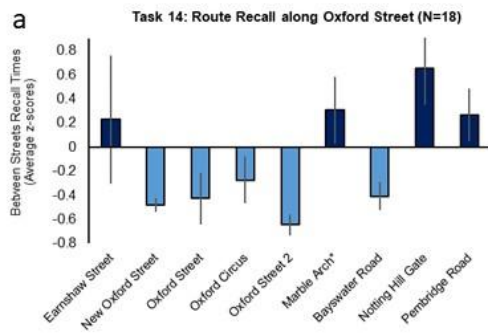


Supplementary Figure 8.2. Log-transformed response times per task. For each task (i.e. run), the density distribution of log-transformed response times were plotted. Fitted distribution (blue line) and normal distribution (red line) indicate a better fit for longer response times due to a high number of very fast response times at the bottom end of the scale.

Summary of Recall: Initial Planning Times

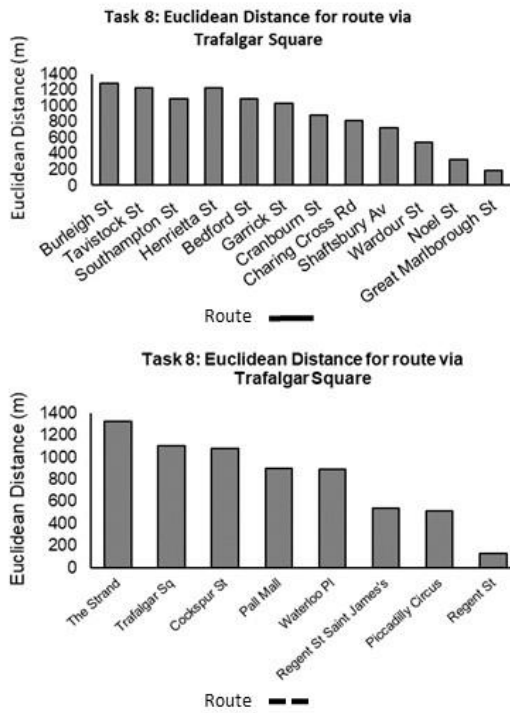


Supplementary Figure 8.3. Correlation of initial planning times and RTs between streets. Initial response times, similar to response times between streets, indicate a high number of fast initial planning events up to 10 seconds and skewed data (a). Log-transformation (b) and z-standardised (c) initial response times indicate a closer fit of normal (red line) and fitted distribution (blue line). Neither of these was correlated to the means of response times between streets (d-f).

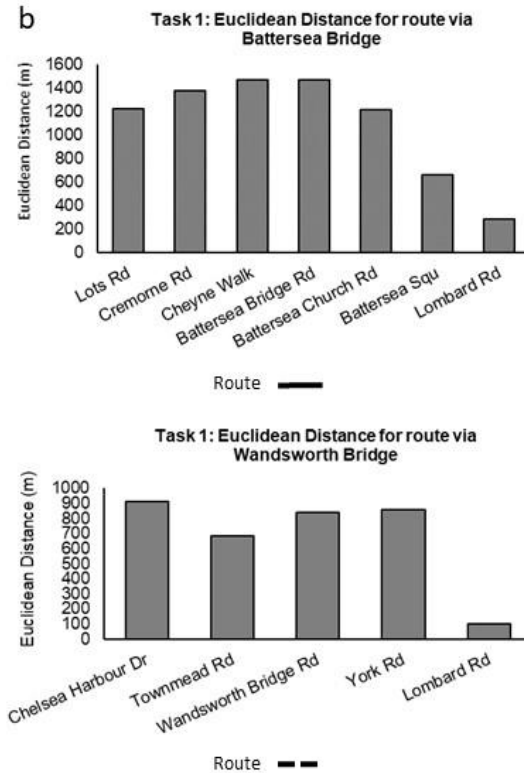


Supplementary Figure 8.4. Additional route recall for linear and diverging routes. An additional selection of routes with high agreement across taxi drivers (see **Figure 4.8**) was visualised. Two more linear routes (a) from Zizzi's St Giles to the Gate Theatre and (b) from Maudsley Hospital to Shoreditch Park showed above average (z-transformed) response times, except for places where the route deviates from the straight line (a), near major decision points (Elephant and Castle) and after crossing the River Thames (b). For routes with a divergence point (c) different response time patterns emerge before the routes bifurcate, but at prominent decision points like Northumberland Avenue for both groups slower response times can be found. Map source: [Mapbox](https://www.mapbox.com/)

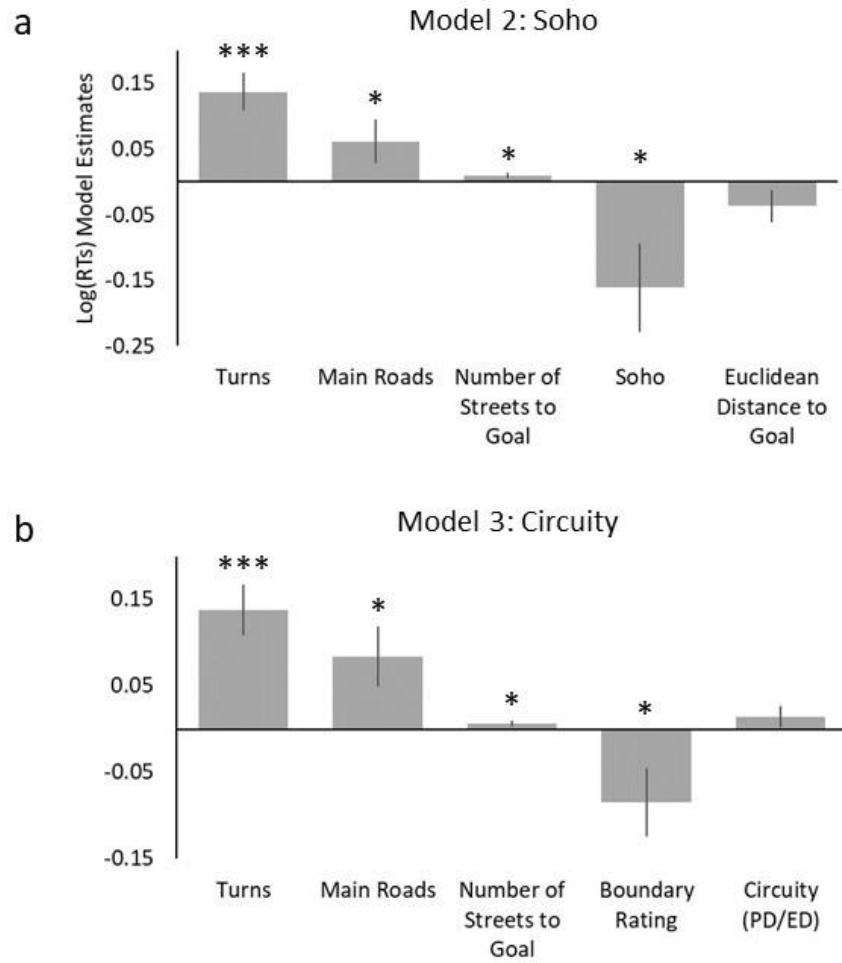
a



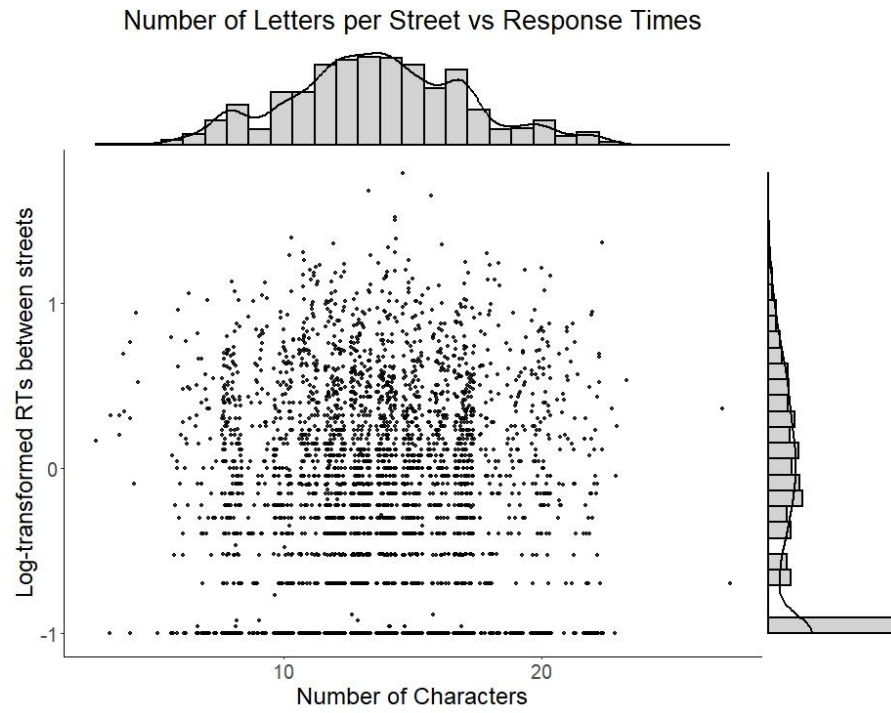
b



Supplementary Figure 8.5. Circuity values. Euclidean distances measured (left) and mapped runs (right) show two different tasks with no detour (a) and a forced detour (b). Euclidean distance along individual streets in tasks that were approaching the destination directly constantly decrease (a), whereas routes with detour character (b) show stages of increasing Euclidean distance a decrease occurs closer to the destination.



Supplementary Figure 8.6. Parameter estimates for alternative models. Two alternative models were analysed in addition to the basic model. In the first alternative model (Model 2), boundary agreement rates were replaced by Soho including its boundaries. In Model 3, Euclidean distance was replaced by circuity, a distance measure with detour character. Both models are in line with the original model and tendencies remain the same.



Supplementary Figure 8.7. Relation between linguistic measures and response times. To account for a potential linguistic impact of the word length on the recall of individual streets, the number of letters were plotted in relation to log-transformed response times between streets. There was no relation between the two variables.

9. APPENDIX A

Interview with a teacher from a Knowledge School in London, UK, about the Blue Book

Int: Interviewer

KT: Knowledge School Teacher

Note: Hesitation markers (e.g. uhm) have been removed from the transcription.

Int: I'm interested in things about... anything that you know about the Blue Book. And how it developed, a bit of history, why it is structured the way it is structured. If you could just tell me then I'll probably ask whenever there's a lack. (0:21)

KT: Well, the Blue Book, as it's called, has been around for over a hundred years. But it has developed. In the year 2000, it was completely redesigned. London had changed dramatically. Some parts of it had not really been covered on the old Knowledge. So, a gentleman from the Carriage Office was tasked to completely redesign the Knowledge. So, what he did is he set about dividing London up into learnable pieces, like the small jigsaw pieces. And after consultation, he realised that a quarter of a mile area was the ideal amount that a person could easily absorb. (1:09)

Int: Was he like a taxi driver himself?

KT: No, he had been, but was an ex-police officer and he was also an examiner at the Carriage Office. What he did was, he divided London up into quarter miles. And when he'd finished this circle, there ended up being three hundred..., six hundred and forty of them. (1:32)

Int: Ok, so he developed the circles across London first and then he decided on connecting them up...

KT: Connecting comes afterwards. Now, from my own personal perspective, I have been to Tokyo with the Japanese taxi corporation. They asked me to show them how they could develop a Knowledge. I also... I turned the opportunity down... I could have gone to Korea and done exactly the same thing. So, what he developed would work in any major city. And that's the thing. I don't think a lot of people realise. (2:00)

[parts omitted to keep anonymity]

KT: It was in the year 2000. Effectively what he did, when he'd finished dividing it up in these bite size pieces, now he did consult with us, and we did say that a quarter mile

was just about right to learn. And when he'd finished covering London in those quarter mile circles, coincidentally, it amounted to 640. Then what he had to set about doing, was making certain that each circle had an overlay with a neighbouring circle. Then he had to ensure, and I will show you some examples in a minute... he then had to ensure that you would leave an area in each direction. So, if we start at Manor House, the first run leaves Manor House and heads towards Gibson Square. So, you'd learn that area of a quarter of a mile around Manor House and you exit the area heading south. Now later on, you come back to the edge of that area to a place call Harringay Green Lanes Station, but you arrive there coming from the north. Is that making sense? (3:17)

Int: Yes, it does.

KT: Later on, there is several other runs in the area and they all leave the area in different directions. Now, the more able candidate will realize this very quickly and he will be able to link together. The less able candidate sees the journeys as individual journeys and fails to make a connection at the start and the end of each run. Is that making sense? (3:46)

Int: Yes.

KT: Now, within each quarter mile, the candidate is expected to learn key places of interest. Now, obviously in the centre of London, there could be as many as forty to fifty places within a quarter mile that need to be learnt. As we move further out to the edges of the six-mile radius, there will be less key points of interest. Now, key point of interest it's pretty obvious. It will always be a hotel, a restaurant, a theatre, large restaurants, religious establishments, anything that the public will need to go to, the candidate is expected to know. (4:25)

Int: You said closer to the centre there are more places than... like more places within the quarter mile radius, rather than further out. But in the Blue Book there are usually about ten.

KT: Right, well that... I'm afraid, I was responsible for that. There is actually eight. And that was again as a result of teaching students and looking at what information they could hold. And we realised that if you gave them more than ten, or more than eight even, they gave up. So, what we decided to do, was to make it a standard eight, as was part of the learning process. Later on, of course, they will then access material which will give them more points in key areas. So, west one (W1) which is the central area of Westminster, will have a lot more points in it, than say E ten (E10), which later, which is at the edge of the map. (5:20)

Int: Ok, but these additional points they learn later?

KT: They will find those at a later stage.

Int: And those eight key points, they are the same for every single knowledge school, (...)?

KT: No, no, no... Knowledge Schools develop their own training material. I developed them based on what examiners asked in the past and obviously on my knowledge of what I felt were the most crucial points within the quarter mile radius of the start and the end of each run. Now, if we move on to the runs, the idea of them is that on a map of London, the roads are coloured orange and yellow. Orange for the major roads, yellow for the secondary roads. The idea of them is that each quarter mile was linked to another one, approximately two to three miles away. And that gave the candidate an opportunity to drive along the orange roads or the yellow roads. The smaller roads, should have been found and learnt at the start and the end of each run. (6:20)

Int: Okay,

KT: Is that making sense?

Int: Yeah, that makes sense.

KT: Now, if you come over here, that effectively is what I've just told you.

[shows map of London with quarter miles, see Figure 2]

KT: If you look at that, that is all of the beginnings and the endings of the runs. If you look at the map closely, you will notice the orange roads and the yellow roads. And effectively all of those roads are covered in the runs, as well as the significant grey roads, which are lesser roads. (6:51)

Int: Okay, do you cabbies have to learn all of the white ones as well?

KT: In theory, yes, in practice, no, it would be impossible.

Int: Okay, I heard from previous lessons, that I mean, if you look at them, the first 80 make up like a first layer...

KT: That's exactly it, yeah...

Int: ...and then a second layer, and then a third layer, and...

KT: I can actually show you the first 80.

Int: Why was it chosen as 80 – 80 – 80 – 80? Like four times 80?

KT: That wasn't. That was us, that was aesthetics. That was the knowledge school dividing it into that system. That's what I've been looking to show you. So, the first 80 for example, that's how they cover. (7:37)

Int: Ah, okay.

KT: Is that making sense?

Int: Yeah.

KT: When you come to the second 80, you'll find that they will start next, and then the third 80 and the fourth 80 and by the time they're finished, there are no grey areas left. So, learning the smaller roads, should really be done, when you're doing your orbit and your quarter mile at the start and the end. Now the course that I developed, the Compass Direction Course, one of the things that I found candidates have a problem with, they learn the roads, they learn where they're going to, but when you take the map away from them, they then have to see the map without it being there. Does that make sense? (8:14)

Int: Yeah.

KT: So, in other words, if you got into my taxi here, outside this building we're in here now, and you said you want to go to Wandsworth, immediately, I have to plot the route, it's not about me knowing the road, but I have to understand the route. So, I developed a system, what's called bullets. So, when the run goes across the River Thames, the 50% bullet would always be the bridge. So, having as attained for our example I would choose Albert Bridge from here. I then got to get myself very quickly something equidistant between here and Albert Bridge, a target, in which case it would be Trafalgar Square. So, my mind says, right, drive to Trafalgar Square, drive to Albert Bridge, and then I'll make the journey much easier for myself, because as I come across the bridge, I can then focus it on Wandsworth. Is that making sense? (8:58)

Int: Yes, makes sense. How are these bullet points connected to the, or are they at all connected to the Blue Book runs?

KT: No, not really, because they're done at an advanced stage. The candidate that will come to do a Compass Direction Course, which I developed, will only come to me having completed all the Blue Book runs, will probably have a substantial knowledge of the points in and around the area. What they will tend to need is this guidance of how to quickly make your mind up about a journey across the top of the map, diagonally down the map or which ever. (9:34)

Int: Do you also use these bullet points for shorter routes?

KT: Not really, no. The shorter runs come just linking up... I'm doing a class tonight with them. The shorter runs, come through linking up the quarter miles, so driving through a few quarter miles.

Int: Okay. So, it's mainly for the long runs.

KT: It's mainly for the longer runs where you have to use bullet points.

Int: And you said you have 50%, usually the river, and then in between...

KT: What I get them to do is, if you sit down and try and think of a journey in one go, it just... it's too much. So, what I say to them is, quick, quickly think of which direction you are going to heading, and then say to yourself, all right, on the map, I've got to go towards that place, be a junction, a roundabout, a bridge, whatever. So, get me there. Then you've reduced the journey in your mind that you've got to view. Does that make sense? (10:32)

Int: Yeah.

KT: So, when you're at the half way mark, then it's much easier to think, ah, yeah, I've got to head towards there now.

Int: Okay. So, coming back to the Blue Book, and the map. So, you said like you started off with Manor House, and then you go down to Gibson Square, from there you leave...

KT:... You link the next run, which is Thornhill Square.

Int: Okay, how far is that away?

KT: Usually they are less than a quarter mile away. (11:04)

Int: Okay, and those quarter mile radiuses then overlap in the beginning and that's where the linking happens.

KT: Absolutely, and that's where you start to learn the backroads by going from the end of one run to the start of the next. That helps you connect it. (11:19)

Int: So, if you would draw all the runs, one after the other, is there like some kind of system like for the first 80, because the first 80 roughly overlap.

KT: No. That's a good question. They are quite random. I have done it to see. But what they do do, they introduce you to all the key orange roads. Although you don't travel along the whole length of that road. What I used to encourage those beginning students to do, was to draw the run on the map, but where you leave a major orange road, get a red pen and just see where you left it to where it would have continued on to. So, one long run for example, number two I think, they came down into King's Cross Road, and then the run took them up a street, called Acton Street, so I used to stop the class to say, right, now with the red pen, I just want you to look to see, although you turn off that major road, I'd like you to understand where it would have gone to. Because later on, they have another run that meets that road further down. Does that make sense? (12:28)

Int: Yes,...

KT: So, I'm trying to get them to connect this bit of it. They leave it here and then they come back at onto it here. But some of them, the lesser able students, don't realise that this road, that they are coming back onto here, was the same road they travelled along up there, because it might have changed its name.

Int: Okay, okay. You said the Blue Book actually, it was like 2000, when they...

KT: It was in the year 2000, when it was completely redesigned and brought up to date.

Int: Okay, and I think they reduced the number of runs... (13:02)

KT: They reduced the number of runs from 480 to 320, but that really was immature, because the lot of the runs were just duplicates. They went exactly the same way. What they... Some of them started in areas that... just give me an example... Belgravia for example, about 30 of them started or ended there, but I think Greenwich had one. So, there is a much more equal spread that you see there. (13:28)

Int: Are there any areas in your experience, any areas that kind of students find more difficult to learn or struggling more with or less, because maybe the blue book runs don't cover those areas well or whatever the reasons?

KT: No, whoever designed this, did an incredibly good job. If you look, the only gaps that are there are parks. If you look, you can see all those circles and the pins. The only space that's left is the green parks. What does happen, some areas because of the complexity of the road layout students do find harder. Psychologically, what has always been interesting to me, if a guy lives north of the river, he tends to worry more about the south of the river, and conversely, the guys that live south, worry about the north, if you live east, you tend to worry about the west. That's a natural phenomenon. (14:22)

Int: Okay, but there is not one area where you can say, this is a very complicated, difficult area?

KT: Well, obviously Westend, central London and the City is always complicated. The City, because of the number of one-way streets that are there and the restrictions imposed upon them. Whereas as you get further out to the edge of the map, there's less one-way streets and less complexity.

Int: But I think wouldn't that be also more difficult for students to learn because it's further out and they don't tend to go there that often.

KT: Well, it's harder for them to pick up points. That I will accept. I think the learning the (...) and street around the area is not too difficult, because if we look at that top run up there, 170 I think it is, there isn't an awful lot there. It's a main road, that takes them

back in. And most of the stuff there is industrial, so I would encourage them to pick up four of five points, there is a train station at (...) road, but apart from that, there isn't a lot there. And if we look in the centre, can you see all those circles where they're overlapping them? That's very, very complex. (15:26)

Int: Okay, okay. What would you improve about this if you had something to, or someone asked you? What would you do?

KT: The only thing I think I would improve would be the examination process. I think, I would probably go back to what they did try once. Where rather than let everybody have learn everything in one go, I might say to them, right, I wanna you come in after you've learnt 40. 40 runs, that's 80 beginnings and endings and if you haven't done them adequately, at that point we can give you corrective assessment. Unfortunately, the examining body doesn't have the responsibility to correct a student and give them guidance. That's where the knowledge school should come into the, you know, formulation, but it doesn't always happen. In terms of the layout and learning, no, I think it's, as I say, I'm full of admiration for the man who came up with this. (16:34)

[...]

KT: Everything I teach, every lesson I do, and I have done for, I mean I've been teaching the Knowledge for now over 20 years, I've always related everything to the Blue Book. Tonight's class, they'll be doing east London with me. And I've listed about 20 Blue Book runs. I'd expect them to be able to give me at least four to six points at the start at each of those runs. But then, what I'd expect them to do to cross connect them. So, for example, Manor House run goes to Gibson Square, but with an advanced student, I would expect them to get me from Manor House station beyond Gibson Square, say to Thornhill Square. So he can work out how the run almost is the same, but then it differentiates towards the end. (17:23)

Int: When you, when you actually do call some runs or plan runs, do you actually use lots of the Blue Book knowledge, linking up the Blue Book runs mainly rather than...? Or does it become more flexible?

KT: Yes, as they get more advanced, it does become more flexible. But certainly, the early candidates, those that were on a 56 day standard, I encourage them to stick as closely as possible to the Blue Book. Because I think the level of Knowledge they've got isn't sufficient for them to always make their own decisions. (17:54)

Int: But later on, let's say at the 21s,...

KT: Obviously, on the 21s it's got to be random, completely random, because they have to be almost a taxi driver. And in 30 years of driving a taxi I think I only ever had two journeys that were remotely Blue Book runs. (18:10)

Int: Oh, really?

KT: Yeah, yeah. Most of the time it's just completely random journeys.

Int: So, would you say that later on, when you really drive a cab, the Blue Book doesn't influence you that much in your driving.

KT: No, it doesn't but what it has done of course, it's given you the ability to know where the streets and roads are going to and where all those places are. But a lot of the journeys that you will then undertake, some of the things you've learnt, will just stay on the back shelf. Simply because of time. Remember, the Blue Book is always done in the straightest line. Sometimes that's not practical. (18:44)

Int: (...) it's very interesting how the Blue Book is constructed, because for us it looks like a big mess. We don't see all those structures that you have (...), but if you would think about alternative methods of learning the Blue Book, let's say you start off in the north west and you learn every single street around that area and then you expand gradually. Or you start off in the centre of London, let's say Trafalgar Square, and then you just expand your circle of learning the map more or less. Would that make any sense for you? It's a different way of learning. (19:29)

KT: It is. And I'm always open to different methods, but I'm so convinced that this works. I would be reluctant to have a system that altered that. I think the danger then starts becoming that people then pick and choose which areas they want to learn. You're with me. And it would be a great temptation to ignore these bits down south and up the north there and people would go to what we call the honey pot, which is the centre. I think they'd spend more time learning that. The idea of the blue book is that it makes you to all these far flung places. (20:02)

Int: So, it would be more flexible, with the Blue Book you're more flexible

KT: Yes.

10. APPENDIX B

The following text is an excerpt from an email exchange with Robert Lordan, author of the Book ‘The Knowledge: Train Your brain Like a Cabbie’ (2018), who has given consent to be quoted on this:

“In terms of planning a route: When a passenger asked me a destination, usually the first thing that would happen is my brain would latch on to the compass point. So for example, say I picked up at St Pancras and somebody wanted to go to Brixton, my mind would immediately orientate its way south.

How I'd then plan the route could depend. If it was a common destination- say for example Harrods or Waterloo station, I wouldn't even have to think; my brain would be on autopilot. With big points it's easy, like a moth drawn to a light!

For longer, trickier routes, I'd find that my brain would often plan in stages; essentially I'd envision a set of waypoints and the route would then come to me as I progressed.

In terms of how my general feeling towards London was impacted: The Knowledge made me crave detail! To this day I want to know as much as I can about London; what story and history lies behind every street.

The city buzzes inside my head which is why I love to write about it. I already loved the city, but in studying it I now love it all the more. It feels like an old, familiar friend.

The Knowledge also makes you want to know as much as you can about new locations that you've never been to before; if I go on holiday for example the first thing I do is study maps of the area as I want to know it and be able to get around said location as efficiently as possible once I'm there!”

11. APPENDIX C

London Areas & Boundaries

Road Classification:

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/315783/road-classification-guidance.pdf

Literature:

Filomena, G., Verstegen, J. A., & Manley, E. (2019). A computational approach to 'The Image of the City'. *Cities*, 89, 14-25. DOI: [10.1016/j.cities.2019.01.006](https://doi.org/10.1016/j.cities.2019.01.006)

General Links:

https://wikitravel.org/upload/shared//b/b6/Areas_of_Central_London_I.png

https://wikitravel.org/upload/shared//a/a3/Areas_of_Inner_London.png

https://www.reddit.com/r/london/comments/7xs7u9/neighborhoods_map/

https://blackteawhite.files.wordpress.com/2013/10/london-map_neighbourhoods_labeled1.png

Regent's Park:

Mappery. (2009, June 30). Regent's Park Map. Retrieved from

<http://www.mappery.com/map-of/Regents-Park-Map>

On The World Map. (2020). Regent's Park Map. Retrieved from

<http://ontheworldmap.com/uk/city/london/regent-s-park-map.html>

Print Club London. (2020). Regents Park Map. Retrieved from

<https://printclublondon.com/shop/regents-park-map/>

Congestion Charge:

Wandsworth.gov.uk. (2019, January 11). Three months to go before new Ultra Low Emission Zone launches in central London. Retrieved from

<https://www.wandsworth.gov.uk/news/january-2019/three-months-to-go-before-new-ultra-low-emission-zone-launches-in-central-london/>

Transport for London. (2013, April 25). Consultation on changes to the Congestion Charging Scheme. Retrieved from

<https://consultations.tfl.gov.uk/roads/congestioncharging/>

City Metric. (2018, March 12). London congestion charge has been a huge success. It's time to change it. Retrieved from <https://www.citymetric.com/transport/london-congestion-charge-has-been-huge-success-it-s-time-change-it-3751>

Hyde Park & Kensington Gardens:

Mappery. (2004, March). London Hyde Park Map. Retrieved from

<http://www.mappery.com/map-of/London-Hyde-Park-map>

Serpentine. (2003). The Two Parks - Evening Route. Retrieved from https://www.serpentine.org.uk/pages/run_routes_02b_index.html

Nicholas L. Garvery. (2011, October 25). Hyde Park and Kensington Gardens. Retrieved from <http://nlq-steampunk.blogspot.com/2011/10/hyde-park-and-kensington-gardens.html?m=>

Bucket List Journey. (n.d.). Stroll through London's Hyde Park. Retrieved June 1, 2020 from <https://bucketlistjourney.net/a-stroll-through-londons-hyde-park/>

Mayfair:

Google Maps. Mayfair. (2020). Retrieved from https://www.google.com/maps?client=firefox-b-d&sxsrf=ALeKk037rCle1FNjxJRK0tXytr5lgZ6fw:1591007075510&q=mayfair+uk+map&gs_lcp=CgZwc3ktYWIQAzIGCAAQFhAeMgYIABAWEB46BAgAEec6AggAOggIABAWEAoQHIDRJ1j0LmCSM2gAcAJ4AIABUIgBqAKSAQE0mAEAoAEBqgEHZ3dzLXdppeg&uact=5&um=1&ie=UTF-8&sa=X&ved=2ahUKEwia6Jigs-DpAhXBYMAKHVg0DooQ_AUoAXoECA4QAw

Wikipedia. (n.d.). Map of Mayfair. Retrieved June 1, 2020 from https://en.wikipedia.org/wiki/Mayfair#/media/File:Mayfair_-_map_1.png

Wetherell. (n.d.). The Neighbourhoods of Mayfair. Retrieved June 1, 2020 from <https://wetherell.co.uk/mayfair/neighbourhoods-mayfair/>

Planned travel. (n.d.). Mayfair. Retrieved June 1, 2020 from <http://www.plannedtravel.co.uk/pageimage/map/Mayfairnm/Mayfairnm.htm>

Soho

Google Maps. Soho. (2020). Retrieved from https://www.google.com/maps?client=firefox-b-d&q=soho+map&um=1&ie=UTF-8&sa=X&ved=2ahUKEwj7o_iZteDpAhX8QEEAHT4nApQQ_AUoAXoECA0QAw

Wikipedia. (2009, December 4). Map of Soho. Retrieved from [https://en.wikipedia.org/wiki/Soho#/media/File:Soho_\(London\)_OSM_map.png](https://en.wikipedia.org/wiki/Soho#/media/File:Soho_(London)_OSM_map.png)

Wikia.org. (n.d.). Soho. retrieved June 1, 2020 from <https://london.wikia.org/wiki/Soho>

On The World Map. (2020). Retrieved from <https://www.google.com/url?sa=i&url=http%3A%2F%2Fontheworldmap.com%2Fuk%2Fcity%2Flondon%2Fmap-of-soho.html&psig=AOvVaw2wT9edFAgeGZf7T19hraQ6&ust=1581419992325000&source=images&cd=vfe&ved=0CAIQiRxxFwoTCJC7wtvuxucCFQAAAAAdAAAAABAg>

Leicester Square

File: Leicester Square map.png. (2015, May 13). Retrieved from https://commons.wikimedia.org/wiki/File:Leicester_Square_map.png

File: Leicester Square OSM map.png. (2015, May 13). Retrieved from https://commons.wikimedia.org/wiki/File:Leicester_Square_OSM_map.png

White Hall

Wikipedia (2012, January 10). Map of Whitehall and surrounding streets, showing government buildings. Retrieved from https://en.wikipedia.org/wiki/Whitehall#/media/File:Whitehall_OS_OpenData_map.png

Research Gate. (n.d.). Whitehall. Retrieved June 6, 2020 from https://www.researchgate.net/figure/Whitehall-Map-by-Emery-Huang_fig2_281406044

File: Map of Whitehall Gardens area 1894.jpg. (2015, January 15). Retrieved from https://commons.wikimedia.org/wiki/File:Map_of_Whitehall_Gardens_area_1894.jpg
Whitehall facts for Kids. (2020, May 22). Retrieved from <https://kids.kiddle.co/Whitehall>

Belgravia

Google Maps. Belgravia. (2020). Retrieved from <https://www.google.co.uk/maps/place/Belgravia,+London/@51.4945705,-0.1661515,14.32z/data=!4m5!3m4!1s0x48760522b70a4ec5:0xbcf21675b596b3b3!8m2!3d51.4982272!4d-0.1535489>
Moving to Belgravia: A Smart Guide. (2017, September 29). Retrieved from <https://storing.com/moving-belgravia-smart-guide/>

Battersea Park

Friends of Battersea Park. (n.d.). The Park. Retrieved 2020, June 6 from <https://www.friendsofbatterseapark.org/the-park>
Battersea Park. (2020). Retrieved from <https://batterseapark.org/home/maps/>
Battersea Park London. (2012, November 5). Retrieved from <https://modernizedcitieslondon.wordpress.com/2012/11/05/battersea-park-london/>

Nine Elms

Google Maps. Nine Elms. (2020). Retrieved from <https://www.google.com/maps/place/Nine+Elms,+London/@51.4778435,-0.1464806,15z/data=!4m5!3m4!1s0x487604fa5f63ca5f:0xe63835b2d6c0ba19!8m2!3d51.4801974!4d-0.1396819>
Mapping out the opportunities in Nine Elms. (2013, September 5). Retrieved from <https://www.constructionnews.co.uk/buildings/clients/mapping-out-the-opportunities-in-nine-elms-05-09-2013/>
Gowen.co. Nine Elms London. (2020). Retrieved from https://www.google.com/url?sa=i&url=http%3A%2F%2Fwww.gowen.co%2Fnine-elms%2Fnine-elms-london-2%2F&psig=AOvVaw2funDHf-KuDSxjeXzvwWfv&ust=1581423753968000&source=images&cd=vfe&ved=0CAMQjB1qFwoTCLC46t_8xucCFQAAAAAdAAAAABAe
Cinematic Geographies of Battersea. (2012, December, 7). Retrieved from <http://cinematicbattersea.blogspot.com/2012/12/villain-of-nine-elms.html>

Southbank

Our South Bank. Landowners' Map. (2020). Retrieved from <http://oursouthbank.com/about-us/estate-map/>
South Bank BID area map. (2020). Retrieved from <https://southbankbid.co.uk/about-the-bid/map-2/>
Mapping London. (2019, July 2). South of the River. Retrieved from <https://mappinglondon.co.uk/2019/south-of-the-river/>

City of London

Google Maps. City of London. (2020). Retrieved from <https://www.google.co.uk/maps/place/City+of+London,+London/@51.5150432,->

[0.1020399,15z/data=!3m1!4b1!4m5!3m4!1s0x487603554edf855f:0xa1185c8d19184c0!8m2!3d51.5123443!4d-0.0909852?dcr=0](https://www.cityoflondon.gov.uk/about-the-city/about-us/Pages/default.aspx)

About the City Corporation. (2020). Retrieved from <https://www.cityoflondon.gov.uk/about-the-city/about-us/Pages/default.aspx>

City of London. (2020, May 28). Retrieved from https://en.wikipedia.org/wiki/City_of_London

File: City of London, Ward of Lime Street.svg. (2015, April 10). Retrieved from https://en.wikipedia.org/wiki/File:City_of_London,_Ward_of_Lime_Street.svg

Vector - city of London, administrative map. (2020). Retrieved from https://www.123rf.com/photo_24061892_city-of-london-administrative-map.html

Kensington & Chelsea

The Royal Borough of Kensington and Chelsea. (n.d.). Draft Core Strategy for the Royal Borough with a particular focus on North Kensington. Retrieved June 1, 2020, from <https://planningconsult.rbkc.gov.uk/consult.ti/draft.corestat.2009/viewCompoundDoc?docid=1365364&partId=1740788&sessionId=&voteid>

Fulham & Hammersmith

Hammersmith and Fulham Borough Map, London. (2017, May 23). Retrieved from <https://www.mapsofworld.com/united-kingdom/london/hammersmith-and-fulham-borough-map.html>

A complete Cycle Network for Hammersmith and Fulham. (2006). Retrieved from <http://hfcyclists.org.uk/spaceforcyclng/complete-cycle-network-hammersmith-fulham/>