Negotiating the Truth: Exploring the Influence of Metadata in Place-Related Group Decision Making

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I hereby declare that this dissertation is all my own work, except as indicated in the text:

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Abstract

The spread of technologies like the Internet of Things has increased data collection and availability to decision makers. This inherently messy and complex data, growing in volume, is being used to inform strategic decision making in settings such as smart cities to monitor, manage, and develop the urban spaces. Commonly this strategic decision making is carried out by multidisciplinary groups under influential conditions such as time pressure and uncertainty. These decision makers are not necessarily experts or trained data analysts, and it's a difficult task to assess the quality of data they are using. Provision of data quality metadata can alleviate issues of uncertainty but present a similar challenge of interpretation by non-experts. Abstractions and visualisations can make this data quality accessible and can improve decision outcomes by tackling uncertainty. An exploratory study establishes a grounding for issues facing decision making groups on a university campus. This first study presented is a series of semi structured interviews run with six members of Higher Education sector capital project management groups. Individual interviews with these representatives of multidisciplinary stakeholder groups produced a corpus for thematic analysis, validating current theory and identifying opportunities for technical intervention. Interview questions were based around; roles and representation, project drivers, working processes, data use, decision support tools, and project challenges and reflections. An experimental study then investigates the design and assessment of a decision support tool that provides decision making teams with a traffic light abstraction of data quality metadata. A serious game approach uses a local pandemic response scenario to explore group decision making and a support tool intervention. A convenience sampling method recruited 9 groups of 4 non-domain experts to use a bespoke browser-based decision support tool and MS Teams to complete a resource allocation task. An ethnographic approach is used to observe the groups in the sensemaking and decision making process. Qualitative focus groups are used after completion of the task to augment interactions with the tool logged during the session and the decision outcomes. The evaluation of the intervention considers the effects on decision outcomes, decision confidence, data trust, and the decision process in a medium-time-pressured vaccination site selection task.

The main contribution is the development and study of a bespoke decision support tool that assesses the impact of a visual abstraction of data quality metadata on group trust in data under a medium time pressure. In an engaging scenario the map-based tool shows how the technical intervention improved trust of non-domain experts in the data used in their decision making, without negative effects that introduction of detailed data quality metadata caused. Detailed metadata on the other hand was introduced to the detriment of decision outcomes, lower trust in data, and lower confidence in the decision made. The abstraction and implementation demonstrated a working method of engendering trust in data under time pressure to novice users of decision support tools and non-domain experts with respect to the data. The research contributes in a qualitative way the agreement across participants on the high trust in spatial and perceived easy-to-collect data, while highlighting the disagreement dependent on metadata abstraction over other data types such as projected datasets.

No difference is found in task performance and confidence in decision outcomes when providing abstracted metadata and no metadata, though both are improvements on detailed metadata. The results show how abstracted metadata encouraged greater data quality assessment and trust building behaviour than non-metadata or detailed metadata groups. A framework for characterisation of decision making settings by the temporality of the data being used and the time pressure of the decision being made is offered for validation. This model could help researchers in identifying and comparing decision making scenarios and related findings, estimating transferability of results and hypotheses. The study also elicited several factors that impacted the trust in data, the influences on how individuals perceive the data source or collection, such as perceived ease of accurate data collection. Recommendations are given for directions of future work that combine the findings of the studies in this PhD with the state of the relevant literature. A selection of models from the related work are reconsidered, and amendments or extensions are recommended to incorporate the findings on data trust and uncertainty from this research.

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A significant portion of chapter 3 is work carried over from a paper entitled, “The Role of People and Data in Complex Spatial-Related Long-term Decisions: A Case Study of Capital Project Management Groups” (Boyes et al. 2022). The material reproduced is added to in this thesis mostly in the discussion of findings and expansion on the directions for subsequent research.

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1. Introduction

Consider a planning group faced with putting up a new building on a university campus that needs to propose the size of rooms to be built into it. To understand capacities of the classes that will be taught in the rooms the group looks at the datasets made available to them. Timetable data for the modules the new building would support suggests that 4 rooms of 50-person capacity are needed and a 300-seat lecture theatre. Space monitoring equipment that records attendance at lectures in a nearby building has captured 50% student attendance against the module sizes over the last 3 months. The group needs to agree how many rooms and seats are needed before the next phase of the project can start. They need to negotiate the conflict in the data sources they've been provided, using their perspectives and the quality of the data, to choose which numbers to adopt in making their decision.

With the development of technology and the expansion of the human population, the availability of big data has exploded. Information overload causes stress and has a negative impact on people's ability to make good decisions (Hahn, Lawson, and Lee, 1992; Marsden, Pakath, and Wibowo, 2006). Decision makers experience information overload when they are presented with more data than they can efficiently handle, and they do so without taking into account the quality of the data they are employing. High information loads can have the same negative impacts as noise, such as mistakes in judgement (Klapp, 1986). Decision making that is inconsistent and group unanimity that is lower are both symptoms of judgement errors (Chewning and Harrell, 1990). Lamb (1991) criticises the constraints on people's ability to assimilate information. Selective attention or filtering is used to process a portion of the information at the expense of the remaining information when the information volume is greater than the capacity of the individual to process it. That remaining information can still be crucial. Information overload and its possibly paralysing effect can make it harder for a decision maker to discriminate between crucial and secondary information in times of crisis or emergency.

Mobility, the environment, the economy, governance, quality of life, and education are among the administrative domains for areas with a growing population. Initiatives that support management and organisation, technology, governance, policy framework, people and communities, economics, constructed infrastructure, and the natural environment are among the elements essential to cities of the future.

Cities have challenges resulting from an increase in; the management of waste, the provision of adequate resources, the maintenance of air quality, various health issues for residents, traffic flow, and the upkeep of infrastructure under the continuously increasing load. Cities need smarter ways to manage their infrastructure and population as a result of urban growth, and one approach to think about smart cities is in terms of sustainability and livability (Chourabi et al., 2012). Studies that examine the concept of a smart city each offer a somewhat different perspective on what defines one. These include; a focus on the use of ICT and an operational standpoint (Caragliu and Nijkamp, 2013), requirement of a complex IoT network measuring and providing information on a large number of systems (Zanella et al., 2014), merging of digital and more traditional physical infrastructures to understand the environment (Batty et al., 2012), a metric-based approach to identifying smartness of cities, and acknowledgement of the variety and looseness of terms used such as intelligent, digital, and smart (Albino, Berardi, and Dangelico, 2015).

A smart city merges ICT with traditional infrastructure, the coordination and integration of which requires digital technologies and strategic decision making (Batty et al., 2012). It is important to draw a distinction between a city that is smart and a city with IT. To make a city smart a gap must be filled between acquiring data and comprehending what is acquired. The usefulness of smart cities as a topic for interdisciplinary study and multidisciplinary discourse should be recognised. IoT in a smart city must be able to integrate a lot of systems and give users access to the right data for digital services. The possible devices, technologies, and related services that can be combined to create a smart city are diverse. New services may be made available to cities, their residents, and their users through the data that could be generated and gathered by devices like monitoring sensors.

A smart city has access to a lot of complicated data that is also rather big, and can have multiple dimensions in their patterns and fluctuate in both time and space. Data can also take on more abstract shapes, or originate from sources that are more difficult to visualise such as social media posts on events or points of interest that are chronologically and spatially related to those of other users. The utility distribution network is one example of a hidden activity or process that has become more complex with the addition of variable renewable sources like solar or wind power generation. These sorts of data are difficult to visualise due to their complexity. Big data and analytics bring with them issues around the usage of pertinent data, as well as cultural norms and data literacy. Lack of data literacy creates a problem with the rising usage of inconsistent quality data in strategic decision making (Xing and Wang, 2021).

Data-based solutions and novel technology are frequently adopted by universities. Campuses resemble small cities because of their accommodations, eateries, retail stores, transportation, security, and professional services; they also face the same issues. For multidisciplinary decision making groups or individuals, this raises dangers and obstacles related to privacy and infrastructure, as well as issues that are comparable to those already mentioned about the interpretation of this data and potential volume. Projects that would develop smarter campuses could be applied to cities with some scaling up. The key is better decision making and services that integrate environmental monitoring with human interaction and control. Strategic decision making that is data-driven and incorporates the interactions of a variety of stakeholders is made possible by intelligent management and services. Managing, storing, and presenting the massive volumes of data from these IoT devices creates issues.

Making sense of the connections that can exist between people, places, events, and combinations of those is a process that is ongoing. It is necessary in order to anticipate change and guide action. The process of developing situational awareness that can be used to inform decisions is known as sensemaking. This is especially necessary when making decisions in complex or uncertain conditions, or a combination of the two (Klein, Wiggins, and Dominguez, 2010). Teams can reach consensus and make choices collectively when sensemaking is used effectively in difficult settings (Pirolli and Russell, 2011). The sensemaking viewpoint has been utilised in earlier studies to analyse the decision making process and the tactics used during the process. The process can be improved, but it can also be hampered or ruined by the presentation of data as part of support systems. Closely related are the act of making sense, situational awareness as a state or outcome, and decision making as a process and action.

Making decisions is a process that involves weighing and choosing between two or more possibilities in light of one's goals, objectives, values, and wants (Hill et al., 1984; Fülöp, 2005). The procedure, which consists of a number of steps, progresses from receiving information, through interpretation and analysis, to reaching a decision. Conflicting information might make decision making more difficult, there may be more contradicting information available as mobile and sensor technology proliferates. Consolidating factors that affect decision making, they can be roughly divided into task- or environment-related factors such as time constraints, risk, and task complexity, as well as system factors like transparency and workload.

Cities are by their very nature interdepartmental, as shown in the planning process for instance. The administration and any function involving interaction with visitors, citizens, or outside parties are interdisciplinary. In order to benefit inhabitants and the smart city, multidisciplinary teams should be encouraged rather than individuals making independent decisions from within the group (Pfeiffer and Naglieri, 1983).

Geospatial or place-related datasets are now used in a wide range of applications such as public health, geology, forestry, transportation, and urban planning. They are now used by decision makers at various organisational levels including operational and strategic , whereas earlier they were primarily employed by geographic information experts (Longley et al., 2005). As a result, more GIS users who are knowledgeable about their application but not knowledgeable about geographic information are using this type of data in their decision making.

Decision making teams can be described with respect to some of their characteristics. They can be dispersed spatially with members kept apart, or they can be collocated with the decision makers occupying the same room or area. The decision making process may be synchronous or asynchronous in the operation. Group membership may consist of members with a wide range of disciplinary backgrounds and degrees of expertise, or it may not be diverse.

These variables may introduce similarities and distinctions that alter how findings are generalised or applied to other contexts. Due to the process-related nature of decision making it is possible for elements to be combined and to alter over time. Understanding these variations simplifies realising the problems and the sources of assistance that might be observed in situations involving decision making. The interaction of these factors in an environment will determine the process structure, its difficulties or pinch points, and its chances for intervention. Multidisciplinary crisis management teams can be distinguished from other teams by the high degrees of complexity and uncertainty that are present in their decision making (Uitdewilligen and Waller, 2018).

The time constraints placed on the decision making groups affect the aspects of a task that groups attend to, with the completion objective being most crucial when scarcity is at its greatest level. Task qualities are important in reducing the negative impacts of time constraints. Task complexity is particularly important. Relating back to the strategic decision making process and data volumes in the earlier context of smart cities and campuses, the complexity that comes with the situation will affect how decision makers react to time constraints. Users of data are likely to take into account just the information that they believe to be most pertinent, which presents an opportunity or goal to direct and assist that behaviour in decision support systems or the presentation of data.

The trust in data and decisions for collaborating groups is of particular interest in understanding complicated spatial-related long-term decisions and the sensemaking processes (Suprapto et al., 2015). The smart city context referenced earlier emphasises that big data insights depend on contextual analysis and that relevant metadata should be supplied to facilitate data users' interpretations. When faced with uncertainty, decision makers may use data of variable quality. When making judgments based on data, the information's quality is crucial because poor data can lead to poor decisions. One method to manage risk and uncertainty is through trust, a different perspective to managing uncertainty in the decision making process.

Accuracy, completeness, timeliness, and relevance are a few criteria that can be used to gauge the quality of information (Wang and Strong, 1996). Regardless of the context in which the data are used, certain aspects such as accuracy and completeness lend themselves to objective measurement. In contrast, the topic of the suitability of using data in a decision making process might be more subjective when it comes to relevance. Researchers have suggested connecting these objective quality parameters to the information used in the decision task so that decision makers have access to this extra information. Such measurements have been referred to as data tags, data quality information, and data quality metadata. Research has shown that provision of quality metadata along with its associated information results in different decision outcomes to when the decision is made using the relevant information alone (Dijkstra, 1999).

By using an intuitive traffic light abstraction, Shankaranarayanan and Zhu (2021) and Devillers et al. (2007) encourage the adoption of data quality metadata visualisation for decision makers. However, these can be combined with other research to explore what other effects visualisation has in the decision making context and its outcomes, particularly when it affects the decision makers' trust in the data they are using. These propose interfaces and test the usefulness in reducing decision makers' cognitive load when using data quality metadata.

Providing decision makers with quality metrics such as data quality metadata can aid them in evaluating and incorporating quality into their process, lowering uncertainty in the data and enhancing trust as part of their decision making. In situations of information overload or time constraints, abstraction or simplification would make this understandable to non-domain experts. Beyond the impact of metadata visualisation on mental workload, what are the consequences on other elements of data users' decision making processes, such as their confidence in the data or the outcomes of their decisions under different time constraints?

The spread of technologies like the Internet of Things has increased data collecting, archiving, and availability to decision makers. These data are being used to inform the monitoring, management, and development of cities as a result of population expansion, a migration to urban areas, and the adoption of technologies. In terms of their size, multidisciplinarity, structure, temporality, location, and other factors that influence decision making, these cities can serve as lenses and settings for examples of strategic decision making across a number of organisations. University campuses provide potential testing grounds for creating and evaluating technology and policies since they are like small cities.

Understanding one's choice space is a prerequisite for decision making, which involves choosing between two or more options. Through a process of sensemaking, both individually and collectively, they reach a condition of situational awareness that permits them to do this. Decision makers need to be able to comprehend, evaluate, and effectively incorporate the data into this process when these decisions are data driven. Factors including information overload, the need to make decisions quickly, the difficulty of the work, the reliability of the data, and uncertainty can affect someones capacity to do this. These also have an impact on decision outcomes and decision maker performance.

To deal with these issues, decision makers use heuristics and decision strategies based on their prior knowledge, the decision support system, and task organisation. For instance, in situations of time deadlines and information overload, decision makers will filter data based on relevance to task completion in order to simplify the issue and produce a result in the time allotted. Decision makers can use data quality indicators, detailed or abstracted data quality metadata (such as provenance, completeness, and accuracy), in this way. It is currently unclear how visual representations of data quality metadata are integrated into group decision making under time constraints, and how this affects both the process outputs and the group confidence in the data used. Decision makers must have trust in the data in circumstances that are inherently messy and overwhelming due to the possibility of growing and noisy data in strategic decision making. The metadata needs to be accessible in the sense that decision makers can be constrained by time and r familiarity with data, and won’t all be data scientists or domain experts that know the subtlety of reliability and expected patterns or behaviour of data.

1.1 Research questions

To explore this area, this thesis poses and addresses the following research questions:

1. To what extent is data used in group sensemaking and decision making process for significant development projects?

2. What are the similarities and differences in the sensemaking and decision making process for teams under different time pressures?

3. What is the effect of presenting metadata in team sensemaking as part of the decision making process?

Auxiliary questions to these ask:

1. How can trust be appropriately influenced during the decision making process?

2. What are the effects of metadata presentation on the decision outcomes and attitudes?

3. How do groups interact with the data and metadata during decision making processes?

1.2 Contributions of the thesis

Given the research questions and motivations of the thesis, several contributions to knowledge are made:

An exploratory study of project management groups, multidisciplinary decision making groups in the context of university campuses, emphasises issues faced by decision makers in context and opportunities for technical intervention to support them. With the volume and role of data in strategic decision making, the issue of trust in datasets perceived to have uncertain accuracy is offered.

The presentation and visualisation methods made it difficult to interrogate the data or test any assumptions, greater consideration should be given for this interaction by individuals and the team to be able to positively impact the collaborative sensemaking process and decision making. Transparency with the fuzziness or the veracity of data was a concern for decision makers, and there is potential that through enabling deeper questioning of assumptions and data, decision makers could achieve increased satisfaction in decisions made. The sensemaking process offers an opportunity to engender trust in the data driving the decision making process. Multidisciplinary teams need to achieve consensus in their decision making, and with these multiple sources of data and their individual perspectives they need to be able to interact with the data both for the individual process but also to support the collaborative group cognition.

A framework for characterisation of decision making settings by the temporality of the data being used and the decision being made is offered for validation. This model could help researchers in identifying and comparing decision making scenarios and related findings, estimating transferability of results and hypotheses.

The main contribution is the development and study of a prototype decision support tool that assesses the impact of a visual abstraction of data quality metadata on group trust in data under a medium time pressure. In an engaging scenario the map-based tool shows how the technical intervention improved trust of non-domain experts in the data used in their decision making, without negative effects that introduction of detailed data quality metadata caused. Detailed metadata on the other hand was introduced to the detriment of decision outcomes, lower trust in data, and lower confidence in the decision made. The abstraction and implementation demonstrated a working method of engendering trust in data under time pressure to novice users of decision support tools and non-domain experts with respect to the data.

The study also elicited a number of factors that impacted the trust in data, the influences on how individuals perceive the data source or collection. Recommendations are given for directions of future work that combine the findings of the studies in this PhD with the state of the relevant literature. A selection of models from the related work are reconsidered, and amendments or extensions are recommended to incorporate the findings on data trust and uncertainty from this research.

1.3 Thesis structure

The following outlines the chapters of this thesis and the work each explores.

Chapter 2

This chapter explores work related to the areas of research covered by this thesis as well as some of the motivations for the directions taken. This review highlights the need to support decision makers handling large volumes of data with uncertain quality. It covers relevant models of the decision making process, and methods for presenting data quality metadata to decision makers. It also demonstrates a gap in the research around the engendering of trust in data as part of the decision making process.

Chapter 3

This chapter looks at an exploratory study carried out with project management groups on a university campus. This setting presented an opportunity for validation of current theory, while indicating opportunities for a technical intervention as part of the research. The study was a series of semi structured interviews with decision makers and provides ground truths that form a basis for interpreting the results of the second study.

Chapter 4

In response to the findings of the exploratory study in chapter 3, and the gap identified in the related work, this chapter presents the motivation and method of data quality metadata abstraction that is explored in the following chapters. This section also justifies the narrowing of time pressure into one area for the purpose of the thesis given the time frame and context of the research.

Chapter 5

The design of a bespoke decision support tool and experimental study is explored in this chapter. It describes the study methodology, the protocol for a team-based time-pressured decision making scenario, and the design of the tool that offers participants one of three conditions; no metadata presented, detailed metadata, and a traffic light abstraction of data quality metadata. The chapter also highlights the data that would be recorded during the study, and how they would be treated and analysed.

Chapter 6

This chapter presents the findings of the experimental study outlined in the previous chapter. Here, the results are stated; decision outcomes, summary statistics of quantitative pre and post task questions, themes emerging from post task focus groups, summary statistics of tool interaction, and artefacts of the decision process. These results are then interpreted in the discussion, synthesising the findings, and returning to the study hypotheses. The findings of this study form a significant contribution of knowledge to this thesis.

Chapter 7

Finally, this chapter concludes the thesis by summarising the findings of the work in the context of the original motivations and research questions. Routes for future research are offered in reflection of the limitations and outcomes of the studies.

2. Related Work

Smart cities offer an example of a source of data that requires decisions. The data are intrinsically spatial and varied temporally, be it historic, live, or projected. Ways are needed to support handling this substantial volume of varied data when decision making depends on it. Work on this and strategic decision making is explored. The relationship and role that university campuses can play in research of cities is introduced. The stance that this PhD takes on sensemaking and situational awareness, and their part in decision making, is presented. Key understanding and challenges in areas of decision making research are explored, before finally presenting a review of the work on metadata, data quality, and uncertainty.

2.1 Strategic Decision Making and Smart Cities

There has been a growth and proliferation of data and big data with advances in technology and the growth of the human population. Smart cities are a developing area of research; in the last century suggestions of how the city of the future could look and operate have spread, and more recently the proliferation of ubiquitous computing is driving cities towards these envisaged environments and exploration of how to implement systems that can make a city smart (Chourabi et al., 2012). Each of these papers that explores the idea of a smart city presents slightly different interpretations of what makes a city smart, including; a focus on the use of ICT and an operational standpoint (Caragliu and Nijkamp, 2013), requirement of a complex IoT network measuring and providing information on a large number of systems (Zanella et al., 2014), merging of digital and more traditional physical infrastructures to understand the environment (Batty et al., 2012), a metric-based approach to identifying smartness of cities, and acknowledgement of the variety and looseness of terms used such as intelligent, digital, and smart (Albino, Berardi, and Dangelico, 2015). A smart city merges ICT with traditional infrastructure, the coordination and integration of which requires digital technologies and strategic decision making (Batty et al., 2012). For the purpose of this research a working definition is presented; "A city that is smart leverages technology to serve people, using an information network to optimise resources, promoting sound and sustainable development”. It is important to draw a distinction between a city that is smart and a city with IT. There’s a gap that needs to be bridged from gathering data to understanding what is collected to make it smart.

Smart cities as a research area have been acknowledged for their popularity as a topic for multidisciplinary discourse and interdisciplinary research (Li, 2019). Interest in smart cities is growing as a response to the complex challenges modern cities face. Administrative domains cover mobility, environment, economy, governance, quality of life, and education. Smart cities often don’t optimally reach their objectives if citizens aren’t involved in their design. Simonofski et al. (2017) show how citizen involvement can transform cities into smart cities through co-creating projects and proactively using city’s ICT infrastructure. Greater access to data by wider populations presents an issue in their ability to usefully engage with and interpret the data.

The performance of a city isn’t just dependent on physical capital but also on its human and social capital. The term smart city can capture production factors of modern cities, notably the information and communication technologies deployed over the last 20 years. City prosperity, measured by GDP per capita in Purchasing Power Parity, was positively correlated with “the presence of a creative class, the quality and dedicated attention to the urban environment, level of education, and the accessibility to and use of ICTs for public administration”. A key point in the summary of the work that found this is that the set of variables described that correlate to a prosperous city experience decay, and therefore need continual monitoring and improvement to ensure that a city maintains sustainable growth and improvement (Caragliu and Nijkamp, 2013).

Factors identified as critical to making a city smart include initiatives that support; “management and organisation, technology, governance, policy context, people and communities, economy, built infrastructure, and natural environment.” Global urban growth and the shift in population is projected to continue for decades. This growth presents difficulties to cities in the management of waste, supply of sufficient resources, maintaining quality of air, other health concerns for citizens, flow of traffic, and maintenance of infrastructure under the continually increasing load. Cities responding to the urban growth are requiring smarter methods to manage their population and infrastructure A way to see smart cities is one of sustainability and livability (Chourabi et al., 2012).

IoT in a smart city should be able to combine large numbers of systems while providing access to suitable data for digital services. There is a huge variety in the set of potential devices, technologies, and associated services that can be combined. Through the data that could be generated and captured by objects such as monitoring sensors or vehicles, new services may become available to cities and their inhabitants and users. A small proof of concept project was run in the city of Padova in Italy. The project explored the collection of environmental data and the monitoring of public street lighting using wireless nodes. Variables such as the CO2 levels, air temperatures, humidity, and noise levels were captured (Zanella et al., 2014).

The data available in a smart city is not just large, but also quite complex. Sources can vary both spatially and temporally, with multidimensional patterns. Data can also take more abstract forms or come from sources that are harder to visualise, for example social media posts about a point of interest or event that are associated in time and space with other citizen posts. Equally, subsurface activities/processes such as the utility distribution network that are becoming more complex with the addition of variable renewable sources in the form of solar or wind power generation. Visualising these types of data presents problems with their complexity, and also the lack of familiarity we have with them as they usually are not visible. Augmented Reality (AR) as an example has been used to enable workers to visualise complex data such as robot applications and software (Collett and MacDonald, 2006).

The use of sensors and IoT devices to provide data streams in a smart city raises issues of the relationship between the data and the space it comes from. For citizens and administrations to use the data they are generating, there must be methods available to help them understand it. The opposed temporalities of big data analytics and urban policy have been identified. Big urban data, the large volume of data we'd see in a smart city or other strategic decision making, generates new hypotheses. But, with this comes a greater degree of and a role itself of subjectivity in the interpretation of patterns in big data (Kandt and Batty, 2021). Big data and analytics raise with them a question of use of relevant data, and cultures and literacy of data use. Without sufficient data literacy, there is an issue in increased use of data of variable quality in strategic decision making (Xing and Wang, 2021).

Capital projects are significant long-term investments and can involve complex decisions when combining factors such as: budgets, the reasons for investment, the range of stakeholders, interdependent projects, and the impacts of construction and the product (Chan, Scott, and Chan, 2004; Xia and Chan, 2012).

The complexity of these projects can be measured (He et al., 2015; Lu et al., 2015). Projects that require strategic decision making gain complexity from the interconnectedness of their components (Xia and Chan, 2012). Complex strategic decision making often requires management groups to be established involving stakeholder representatives. These teams are inherently multidisciplinary with the expected advantage of an increased knowledge pool but a challenge of potentially more variable levels of expertise, or more spread domain expertise when it comes to data analysis and interpretation.

Decision support systems can overcome difficulties like technical and financial challenges. Multi-sensor infrastructure will need decision support systems. Decision makers must be adequately supported with detailed data and, where needed, expert advice. Interpreting and managing information for decision making is becoming an increasingly critical task in discussion of these cities of the future. The effectiveness of decision tools in implementing a comprehensive domain knowledge can be restricted to experts (Aiello et al., 2018). In reviewing strategic decision making literature paradigms, Eisenhardt and Zbaracki (1992) conclude strategic decision makers are boundedly rational. Not all the people that will engage with data are strategic decision makers.

Smart cities offer opportunities but the volume and variety of data that would be fed to decision makers presents a significant issue. Information overload leads to stress and is detrimental to the quality of decisions that individuals can make (Hahn, Lawson, and Lee, 1992;, Marsden, Pakath, and Wibowo, 2006). The overload of information occurs in decision makers when they receive a greater volume of information than they can effectively process, and will neglect to consider the quality of the information they are using. High volumes of information can lead to the same effects as noise, such as stress, distraction, and crucially, errors in judgment (Klapp, 1986). Judgment errors are accompanied by inconsistent decision making and lower consensus in groups (Chewning and Harrell, 1990). Lamb (1991) faults the limitations that are seen in a person's capacity to process information. When the information volume exceeds the person's capability to process it, selective attention or filtering is recruited to process a portion of the information, at the expense of the rest. That remaining information could still be relevant, or even critical. In crisis or emergency situations, information overload and its potentially paralysing effect can make it increasingly difficult for a decision maker to distinguish between vital and secondary information. Studies such as those by Schultz and Vandenbosch (1998) have found information overload to damage decision quality while not under conditions of stress.

This proliferation of sensing technologies and growth of data to drive decisions and operation in cities of the future presents stark issues for the decision makers in the process. From potentially broad and wide ranging backgrounds and areas of expertise, decision makers will need to process and interpret large volumes of data of varying types and quality. The data could be messy, but the individuals and groups need to be able to use it in their strategic decision making.

2.2 Smart Campuses

Parallel to the growth of interest in smart cities is the increased appreciation for the role university campuses can play in the research. Campuses, through a range of their qualities, can be valid test beds for research and evaluation of smart city technologies and paradigms.

Universities often embrace novel technology and data-based solutions. Their accommodation, food and shopping outlets, transport, security, and professional services make campuses small-scale cities, and they address similar challenges. Researchers asking how the data inherent in this ecosystem can be used leveraged the campus user experience to suggest the data should be made publicly available to bring more benefits to the campus. This presents risks and challenges with privacy and infrastructure, and similar issues from the last section on the interpretation of this data and potential volume for multidisciplinary decision making groups or individuals to deal with (Vasileva et al., 2018).

Muhamad et al. (2017) summarises the prevailing condition of smart campuses, their features, and the technologies that support or underpin this smartness. Data entry is covered with contactless technology, IoT supports easier ways to report the status of the environment in real-time, and cloud computing can help organise information and provide data services for these strategic decisions by individuals and groups. These present the same problem again, anticipating the issue of volume of data and the presentation and interpretation by varying levels of expertise or familiarity by users.

The concept of smart campuses aligns well with the smart city literature, and potential initiatives that would aid in realising smart campuses could translate to cities with a little upscaling. Improved services and decision making are key, combining monitoring of the environment with interaction and control (Min-Allah and Alrashed, 2020). Some consider IoT at the root of smart campuses. Intelligent management and services enable strategic decision making that is data driven and that blends the engagements of a range of stakeholders. The large streams of data from these IoT devices bring challenges of data management, storage, and presentation for it to be useable (Yang et al., 2018; (Sari, Ciptadi, and Hardyanto, 2017).

The attention to smart campuses as a basis for research embraces their multidisciplinary nature, and the reflection of the groups and organisations that would be characteristic of smart cities. Dong et al. (2020) present examples of data integration from IoT through GIS and the Cloud to decision makers and end data users. The data were supporting operations such as people, vehicle, and asset management. The main features of these integrations were context-awareness, being data-driven, use of forecasting, user immersion, and decision maker collaboration. In a more specific example of research on campuses for translation to cites, Vieira et al. (2019) explore parking on campuses and user demand. This approached the identification and communication of free spaces using sensors and mobile applications.

The university campus infrastructure and range of users means that decisions are made at differing levels of spatial granularity. Spatial contexts introduce complexity to decision making in groups (Dayeh and Morrison, 2020; Vincent et al., 2019). Combining this with the range of backgrounds and experience of team members, there is a need for clear focus and goal priority for projects as found with similar projects in the literature (Scott-Young and

Samson, 2008). It is suggested in some research on success factors of project management that the human factors are woven into management factors leading to decisions (Cooke-Davies, 2002). Its critical the usability of this volume and variety of data is supported for the effectiveness of the decision makers.

2.3 Sensemaking and Situational Awareness

Sensemaking is a process of continual effort to understand the connections, in order to anticipate change and inform action, that can exist between people, places, and events, and combinations of the three. Sensemaking is the process to achieve a state of situational awareness that can be recruited to make a decision.

Dervin (1998) is a proponent of Sensemaking with a capital S and “knowledge as a verb rather than a noun”. In a discussion of implications for knowledge management, Dervin provides a framework for user studies in line with this knowledge as a verb, giving the foundations of Sensemaking methods as “time, space, movement, gap” or “step taking, situation, bridge, outcome”. There is a sense of movement in all this, the point being driven home by the paper. Information and knowledge are created, sought out, used, and rejected, and users bring these about in different ways. Sensemaking criteria from individuals varies and the degree of this movement described above changes, “for example, when users are evaluating answers from knowledge sources that they found not useful, they focus on system criteria (e.g. credibility and expertise) but when they evaluate answers they found useful they turn to time-space-movement (e.g. getting new ways of looking at things, unearthing causes, moving toward destinations)”. In just reading that there is a sense of change of movement.

This is process to achieve a state of situational awareness is particularly required for decision making in situations that are complex, uncertain, or a mixture of the two (Klein, Wiggins, and Dominguez, 2010). When successfully carried out in complex situations, sensemaking enables teams to reach levels of consensus and to make decisions together (Pirolli and Russell, 2011).

Klein et al (2007) give us aspects of sensemaking: “initial account people generate to explain events; elaboration of that account; questioning of that account in response to inconsistent data; fixation on the initial account; discovering inadequacies in the initial account;

comparison of alternative accounts; reframing the initial account and replacing it with another; deliberate construction of an account when none is automatically recognised". These features of sensemaking have their own traits that need to be considered when designing to support the process. This paper discusses the data frame theory, and the way that sensemaking is a process of framing and reframing. Here a frame is "a mental structure that organizes the data and sensemaking is the process of fitting information into that frame, frame is an explanatory structure that defines entities by describing their relationship to other entities". Simultaneously, data identify the frame relevant to the individual while the frame determines which data are focused on. Klein et al explain how anchors are key to framing, that a few anchor points bring attention to a frame, and that can then bring attention to the data. In designing support for sensemaking individuals and groups, this ongoing frame and reframe process points to a risk but also an opportunity. If a frame can organise the relationship between data, and an anchor point can help to infer the frame, then anchor points can be designed to provide support. A risk, the authors describe how "attempts to improve judgment and decision quality by increasing the amount of data are unlikely to be effective as supports to the evaluation of data". Data overload is a persistent concern. Care must be taken when design anchors or others support in this data frame model.

Taking this idea of risking data overload by trying to improve decision making with introduction of further datasets, consider the cost structure of sensemaking. Russel et al (1993) present a learning loop complex to represent the processes undertaken during sensemaking. Different subprocesses of sensemaking that are described in this complex require different cognitive resources. The nominal starting point of the loop is a search for good representation, a progression of trying to encode information while finding what doesn't fit. Readjustments can take place in the representation to make more fit, in a similar way to the frame and reframe described above. This "representation shift loop" is a good target for supporting improved sensemaking. Improvement in this case being a reduction in the cost of the processing task. The main cost in decision making tasks is extraction of relevant data, and is most time consuming. Interventions could improve the efficiency of data extraction, and subsequently reduce the cost in the overall sensemaking process.

Previous research has used the sensemaking perspective as a way to study the decision making process and the strategies employed during the process (Richter and Arndt, 2018), and describes naturalistic decision making that develops situational awareness through the process of sensemaking (Baber, Fulthorpe, and Houghton, 2010).

This process starts with what Weick et al. (2005) call “noticing and bracketing”. This step is an anchor in what follows. The bracketing of what is noticed is a framing step as referenced from Klein et al. (2007) though not necessarily of just data, it can be the bracketing of the situation and events as they are organised by the individual. That first bracketing, the first framing, begins the work of organising and labelling that influence members of a group finding common ground. The labels enable representation shifts. This first notice and bracket is important then in assisting effective sensemaking, for an individual or a group. In another way, “when information is distributed among numerous parties, each with a different impression of what is happening, the cost of reconciling these disparate views is high, so discrepancies and ambiguities in outlook persist”. This is the group sensemaking and decision making setting. Groups organise through the communication of their noticing, bracketing, presumptions, and actions. This communication isn’t always explicit, bracketing and presumptions can be baked into questions and comments shared within the group. In successfully reconciling those disparate views there is a continued process of drafting and redrafting a shared emergent story, one that becomes comprehensive and includes the appropriate data.

Information systems and technology influence sensemaking and can be used to support it. In supporting that process, decision making can be supported. The presentation of data as part of support systems can improve but also hinder or damage the process (Seidel et al., 2018).

Pirolli and Card (2005) present a process flow approach to the task of sensemaking. Against the axes degree of effort and degree of information structure they create an account of the flow of data and processes. Each data step flows back and forth through process flows, such as external data sources being search and filtered into the next step, while returning to the external data step for further data. The overall flow shows the journey of data from the rawest state through to a structure suitable for communication and further action. Pirolli and Card turn their attention to leverage points for further research and interventions, with a focus on sensemaking that involves large quantities of data, scenarios that are susceptible to data and attention overload. As with Russell et al. (1993), this framework concerns itself with discussing interventions around their effects on the leverage points in the process. The idea of cost returns in this case around that of exploration, enrichment, and exploitation. In scanning, recognising, and selecting data for attention, a shift of attention control or further data foraging has a cost to it in the sensemaking process. Summed up, “it will generally be desirable to explore as much of the information space as possible (because there may be a cost to missing something novel in the data) but this comes at the cost of having to actually work through the material and eventually exploit it”. An important result of the flow described by Pirolli and Card are the two loops they draw out, foraging and sensemaking. As with the leverage points, these direct attention for those seeking to support sensemaking and decision making, whether for individuals or groups. The analysts in their study spent considerable time in the foraging loop, the stage of seeking more relevant data in that information space described above. This searching, and assessing whether relevant, takes time, and this is a cost of the process. Ways that help the searching or sorting of data such as highlighting, or “pre-attentive coding”, can reduce these costs.

There is a tight interplay between the process of sensemaking, the state or product of situational awareness, and the process and action of decision making. A clear understanding of this provides direction for interpreting findings and in support system design decisions.

2.4 Decision Making

Decision making is an activity resulting from a set of two or more alternative choices, options that need to be considered and selected based on goals, objectives, values, and desires (Hill et al., 1984; Fülöp, 2005). The process, a series of steps, moves from information reception, through interpretation and analysis, to a resolution (Eilon, 1969).

Decision making can be induced when there is conflicting information. With mobile and sensor technology proliferation there is potential for greater levels of conflicting information. One paper consolidates the literature on this while identifying factors that influence the decision making process. These were split broadly into: system factors such as; reliability, transparency and workload, the individual factors of; experience, system trust, and training, and task or environmental factors of; time pressure, risk, and task difficulty (Carroll and Sanchez, 2021).

Padilla et al.)2018) offer a cognitive perspective of decision making using visualisations. The paper proposes an integrative model that helps guide areas of exploration and recommendations for designers of visualisations such as identifying critical information needed for the task and encoding this visually. The visual encoding directs the user attention to this information that is determined as critical.

Individual knowledge development is the process of individual team member conversion of data into knowledge about the situation at hand. The process includes collecting, fusing, filtering, representing, and displaying knowledge produced in a format that can be shared (Letsky, 2008). Decision making and situational assessments are cognitive activities that can be performed by teams, and the cognition behind the activity traditionally is approached from individual knowledge and the distribution of knowledge across team members. Theory of interactive team cognition argues that the cognition resides in team interactions and is an activity that takes place in a rich context needing measuring at a team level (Cooke, 2015).

There has been research into multidisciplinary teams in a number of areas exploring the function of the group and the requirements of a successful interaction between members. In contexts, suggestions were made for methods to maintain effective functioning of the team (Kovitz et al., 1984; Fleming and Fleming, 1983). The operation of cities, for example in the planning process, is inherently interdepartmental (Chadwick, 2013; Lichfield, Kettle, and Whitbread, 2016). The administration and any activity engaging with external parties, citizens, or visitors is multidisciplinary. Work has demonstrated the benefits of multidisciplinary teams versus independent decision making of individuals from within the group (Pfeiffer and Naglieri, 1983), and so for the benefit of citizens and the smart city this should be supported. Research has demonstrated that there is a role of the larger institutional setting on individual projects, and it is also a resource in team decision making (Dall and Sarangi, 2018). In multidisciplinary team meetings there is an influence on discussions of the expertise of individual members, this can direct the mapping of roles and responsibilities of individuals in the team onto the decision making (Lanceley et al., 2008).

A case study of opportunities to support factors such as coordination in projects and consensus reaching in team decision making is offered (Geraldi and Adlbrecht, 2007), with significant effect of information load in web-based spatial decision making on the level of and proximity of consensus to individual solutions (Jelokhani-Niaraki and Malczewski, 2015).

Geospatial or place-related datasets are now used in a wide range of applications such as public health, geology, forestry, transportation, and urban planning (Longley et al., 2005). They are also used by decision makers at different levels of an organisation such as operational and strategic levels, whereas previously they were used mainly by experts in geographical information (Longley et al., 2005). Consequently, there are now a greater number of GIS users who are experts in their field of application but not in the geographic information domain, using this sort of data as part of their decision making process. (Alessandra, Valese, and Natta, 2022) presents an example of how designing public open spaces in cities has been explored by this area of research. The focus is on the presentation of geospatial analysis and GIS technology in a participatory process with an inherently multidisciplinary group.

Geospatial data has been used to support decision making processes and planning for response to events, or implementation of infrastructures ahead of potential events with the aim to improve the safety and livelihood of citizens. For example, in response to risk of heat waves and fires (Eskandari and Chuvieco, 2015; Wilhelmi, Purvis, and Harriss, 2004). Some of these data are described as volunteered geographic information and provide a case for remaining aware of biases in the use of technologies for smart cities (Hecht and Stephens, 2014). A strength of the geospatial aspect is the additional context it provides to information, but this presents a challenge in the integration stage of data to avoid loss of context and detail, from both people and sensors. (Sagl, Resch, and Blaschke, 2015)

Cartography and the representation of geographical data has been well explored, looking at the challenges of complex systems or data sets and visualisation in a way that is appropriate and effective for the user (Kraak and Ormeling, 2020). Commonly this research has been on 2D maps, supporting the efficient use of the data representation. Complex networks and large datasets generate challenges in their 2D visualisation, and benefits of cartographic analogies have helped understanding even non geospatial information (Guimerà and Nunes Amaral, 2005). The understanding of handling these datasets and networks should be translated to the challenge of data integration and representation of multiple large data sources on a 3D display. Three dimensional models take advantage of human stereo vision, communicating spatial form of different types of data. 3D models are able to be manipulated to provide alternative perspectives, or for larger objects people can move physically around to rotate for a new perspective. This intuitive interaction enables users to gain a sense of the 3D structure. The natural frame of reference from a 3D model can provide a good platform for complex patterns, spatial and temporal, with an understanding for the user of distances, slope, and relative positions of points and areas of interest (Chadarevian and Hopwood, 2004).

Research has gone into the use of projection augmented relief models (PARMs) as a mapping tool, into the behaviour and interactions they enable. Explored is the benefit to understanding of information from spatial representations (Priestnall et al., 2012). Interactions explored by these table-top displays so far have included the manipulation of the terrain by users (Leithinger and Ishii, 2010), but little in terms of using the model as a method of interacting with visualised information, beyond observing a presentation of data. Augmented Reality (AR) has been combined with relief models to provide responsive tangible surfaces using the Unity3D game engine to process interactions (Rossi, Petrucci, and Olivieri, 2014). The focus of this was to allow a degree of interaction with a virtual tour with interaction through a natural user interface, a finger detection device for scrolling. The AR aspect is a smartphone providing 3D visualisation of historic buildings as the user explores the city.

While relief models such as PARMs can aid understanding of a space, they are limited by the physical model. The built model has a set scale for the visualisation, which presents a challenge should users want to look more closely at subsections of the chosen area, or to look more widely at the area the model sits in, such as a model of a borough in the full context of a city. Independent of the model scale, some of the data that can be visualised on a standard flat map become disrupted on relief models. Terrain and environment changes can cause a line joining two points on the map to become distorted as it maps onto 3D space.

An example of group planning for emergency situations is the logistics in flooding scenarios. Tools are developed to aid groups making decisions in preparation to respond to flooding, using modelling of several variables such as resources and infrastructure. The geographic information system presents a PC-monitor-based display of risk areas and relevant variables (Chang, Tseng, and Chen, 2007). This scenario highlights an example area that could potentially be assisted by the introduction of tangible displays augmented by geospatial data.

Effective use of ground infrastructure is critical to operation efficiency. Algorithms have been developed such as in air traffic control support to help decision makers. These decision support systems can help improve this efficiency but could affect mental workload, and with it their situation awareness and task performance. Research has identified human behaviour in the decision process to find opportunities to enhance the decision support systems and their design (Argyle et al., 2018). Technology being used to support decision making should be sufficiently invisible, meaning it is not being disruptive or interfering with the primary activities of the users (Baber, Fulthorpe, and Houghton, 2010).

Decision making teams can be characterised by various factors that describe them. Spatially, they can be distributed with members separated or collocated, with the decision makers in the same location or space. Temporally, the decision making process can be synchronous or asynchronous. Composition of groups can be largely singular disciplines and expertise levels, or highly diverse in disciplinarity and experience. These variations can bring commonalities and differences that change how findings can be generalised or transferred between settings. The process aspect of decision making means that it can take on combinations of these and change over a period. They don't have to be mutually independent. Appreciating these differences means it's possible to understand what sort of challenges or support can be seen in decision making scenarios. The interplay of these dimensions of a setting will guide the structure of the process, the challenges or pinch points, and therefore will influence intervention opportunities. In the team setting, multidisciplinary crisis management teams and their decision making can be characterised by the high levels of uncertainty and complexity that are seen in them (Uitdewilligen and Waller, 2018).

Ham, Jung, and Park (2021) give an analysis of team decision making and importantly draw out factors that affect performance. The conceptual model they proposed in figure 2.1 highlights the interaction of the elements and phases of the process, though the single direction of the arrows is limiting. Typical issues they found that challenge the process in the context they studied were: "uncertain accident progressions, adverse environments, insufficient and inaccurate information, long duration of accident progression, and weighing up the pros and cons of several options with unclear trade-offs." The third and fifth of those being the most generalised factors, the insufficiency and inaccuracy of the information decision makers had and their task of trade-off assessment. Not apparent in the elements of this decision process model are data and metadata. The elements and their definitions don't explicitly list or assign data to any part of the inputs or process.

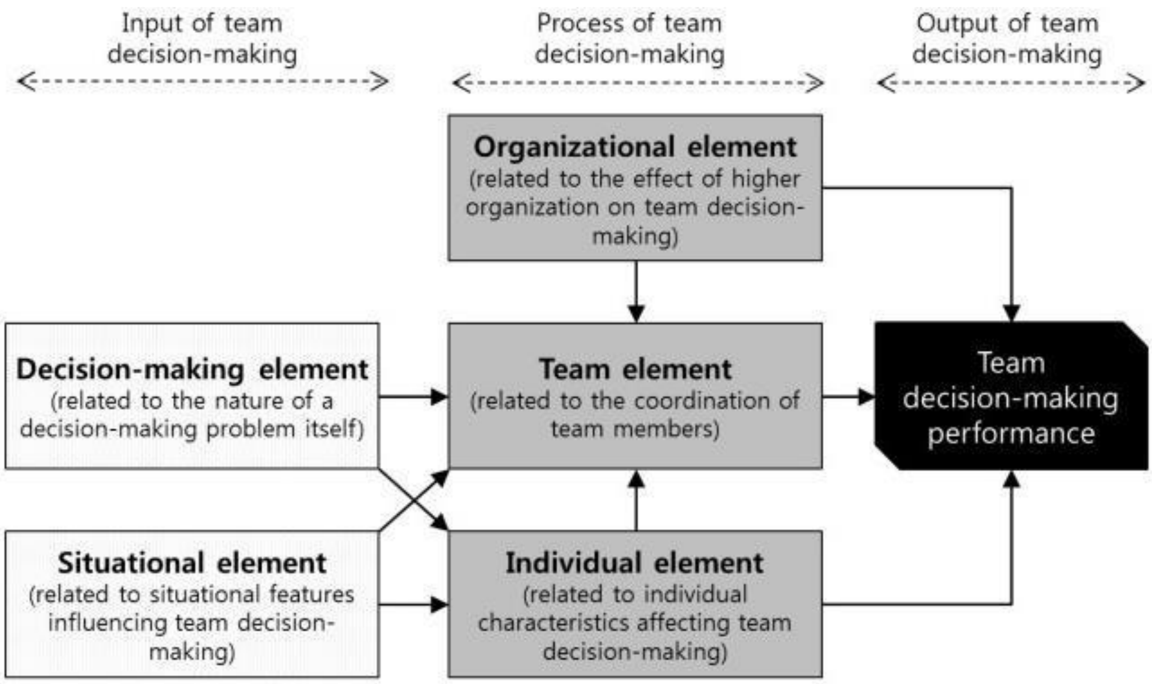


Figure 2.1 Conceptual Model of Decision Elements and Phrases Presented By Ham et al. (2021)

In the context of tactical training sessions for officers, research considered the influence of expertise and experience on decision making. The interest here was in the differences between information modalities such as visual and auditory, and found increases in visual processing capacity but reduction in phonological processing capacity with experience. This gave insight on training and policy towards the demands placed on these decision makers (Roberts and Cole, 2018). Perception of this experience and associated competence can matter. In a competitive environment, where there are team members with information that others don't have access to and that they need to share for a successful or accurate solution as a team, it was found that the less competent individuals shared more information. However, decision accuracy was only better under a cooperative environment (Dayeh and Morrison, 2020)

Taking the situational element from Ham et al. (2021) above, a further characterisation to add to a decision making scenario is the time pressure or time scarcity of the decision. This dictates the temporality of the decision making process. There is a time required to make a decision, and a time available to make it. The pressure is a result of the sense of the time needed to complete the process and the availability to do so, or to do so sufficiently well. Both of these can vary. The time needed to make a decision, to complete the steps of the process, can be lengthened by factors such as the data quantity, problem complexity, and familiarity of/with the data and the domain. Researchers have differentiated between the time constraint and time pressure; time constraint as a specific time allowed and time pressure as a subjective response to that specific time. Time is a resource, technology lets decision makers access and process more data in the same time period, but decision makers also adopt heuristics to handle the quantity of information in the time available to them. These heuristics can include screening out pieces of information to reduce the time needed to process them and to reach a decision, and weighting importance of variables to decide with (Ordóñez, Benson, and Pittarello, 2015).

Time pressure and completeness of information can be influential for decision makers. Ahituv, Igbaria, and Sella (1998) look at a simulation system to train commanders in the use of defensive resources. They observed in simulation sessions the effects of time pressures and completeness of information on how the top commanders performed, interested in the variables; information completeness, constraint of time, and performance differences. Complete information usually improved how they performed, but under time pressure the less experienced commanders didn’t improve performance with complete information. Across experience levels, time pressure often impaired performance.

Drawing together research on group performance and time scarcity effects, Karau and Kelly (1992) explored decision making under 3 time conditions: scarce, optimal, and abundant. Time was inversely related to the focus shown to the task by groups. The time limit imposed on the decision making groups influences the elements that groups attend to in a task, with the completion goal most important when scarcity is at its highest level. Task characteristics matter in moderating the effects of time scarcity. Particularly, complexity of task matters. Returning to strategic decision making and volumes of data in the earlier context of smart cities and campuses, the complexity that comes with this will influence how decision makers respond to restrictions on time to make a decision. Data users are likely to consider only data that they deem most relevant, which brings an opportunity or aim to guide and support that behaviour from users in decision support systems, or simply in the presentation of data. The key contribution of this paper by Karau and Kelly is an attentional focus model that captures the above. The model directs areas of research that can manipulate data attributes such as importance, relevance, and the impacts of the interaction process and data quality communication on the group decision.

The attentional focus model predicts that “time pressure should lead group members to focus on a restricted range of task-relevant cues and to adopt task completion as their major interaction objective” (Karau and Kelly, 1992). In subsequent research, how decision makers will do this is explored (Kelly and Loving, 2004). A filtering process is adopted when time pressure is increased, though the relationship with the decision making group is complex given the task demands and group structure. Time pressure helps to focus a group onto the task completion during decision making, but this can be detrimental as well as beneficial. The positivity of this impact is dependent on which elements of the decision task are important. The time pressure alters the information that individuals select and offer in the group discussions. This filtering process offers opportunities for support in decision making by guiding and assisting beneficial or appropriate filters. It’s suggested in this paper that interventions should “focus on improving and expanding information processing, rather than improving information search.”

Further research of team decision making under varying time pressures explored effects on the communication in groups. Vertical structuring is the organisation structure of groups, for example managers related to employees. There are strong effects of time pressure of a decision task on the vertical structuring of groups. Under conditions of high time pressure, low time availability to complete the task, group members share air time less equally than in low time pressure. The difference in communication from the most to least communicative members in a group is increased with time pressure. In these situations, team members also reported more prominent leadership. Greater group agreement is caused by the time pressure in order to reach consensus as a team that is required for a decision (Isenberg, 1981).

The area of time pressure and information overload effects on decision making is well trodden. Studies show stress impacts decision making and decision support systems proposed to mitigate these effects of stress. Phillips-Wren and Adya (2020) re-tread some of this but highlight how most work looked at time pressure and information overload as stressors, they add complexity and uncertainty to the category and provide a useful model (figure 2.2) of how this interacts with decision quality.

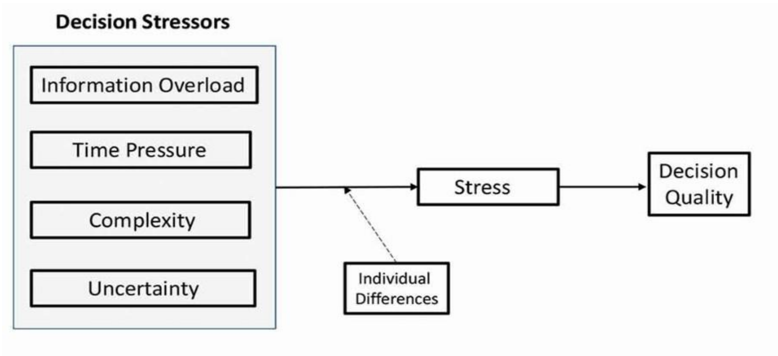


Figure 2.2 Conceptual Model of Decision Stressors Presented by Philips-Wren et al. (2020)

Decision makers can be accustomed to using summarised and aggregated data in their decision making through decision support systems, or in environments similar to those discussed in smart cities as a result of large networks of sensors. Highly detailed information can lead to overload for the decision maker, reducing their ability to process the data. Aggregation reduces the amount of data the decision maker needs to directly examine, but this can also remove details that they want to access. Speier-Pero (2019) looked at effects of time availability, information presentation, and decision task strategy on the performance of decision makers. Presentation being detailed or aggregate information, time being limited or sufficient for the task given, and strategy being compensatory or non-compensatory. When the information made available to decision makers exceeds their cognitive capacity, or exceeds the time available for processing, information overload becomes likely. Aggregate information therefore is beneficial in limited time conditions. The presentation in aggregated form is suggested to support decision makers in ongoing time pressures though supplementing with detailed data when there is available time or more precision is required. In addition to the decision outcomes, the limited time influences the way in which decision makers process the information. A useful model of the interaction of the effects is presented by the paper, which is shown in figure 2.3.

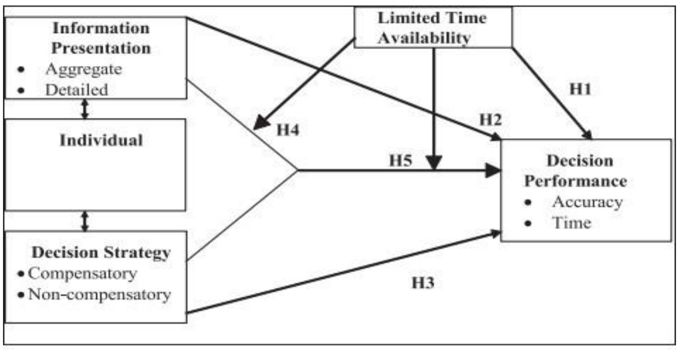


Figure 2.3 Conceptual Model of Interaction Effects of Decision Factors Presented by Speier-Pero (2019)

2.5 Data Quality and Metadata

Of particular interest in understanding complex spatial-related long-term decisions and the sensemaking processes is the trust in data and decisions for collaborating groups (Suprapto et al., 2015). Smart city work introduced earlier points out that insights from big data rely on contextual analysis and that to aid interpretation by data users, relevant metadata should be included (Kandt and Batty, 2021). Decision makers can be using data of varying quality under a state of uncertainty. In data driven decision making, quality of the measurement information is critical, wrong decisions can result from low quality data (Petri, Carbone, and Mari, 2021).

The improvements to information technology, sensing and data capture capabilities of sources such as IoT devices, have facilitated organisations to collect, store, and use more data than ever before. This data, which serves as an input and critical aspect to strategic decision making, is processed and presented in a range of ways to serve the purpose of the organisation. With the data volume increase is an increase in the complexity of management and subsequently the risks of ensuring or maintaining data quality (Raghunathan, 1999). Poor data quality can also damage organisational reputations, their capital expenses, and increase exposure to risk (Hodson, 1997). Data quality is crucial to decision making amid the growth of sensing technology being deployed (Loebbecke and Boboschko, 2020). Data quality is therefore important for both practitioners and researchers.

Information quality may be measured along many dimensions such as accuracy, completeness, timeliness, and relevance (Wang and Strong, 1996). Some of these dimensions such as accuracy and completeness lend themselves to objective measurement, innate to the data itself, regardless of the context in which it is used. On the other hand, relevance could be more subjective in discussion of fitness of use of data in a decision making process. Researchers have proposed that these objective quality dimensions should be linked to the data used in the decision task, providing decision makers with this additional information. Such measurements have been referred to as data tags (Wang, Storey, and Firth, 1995), data quality information (Chengalur-Smith, Ballou, and Pazer, 1999; Fisher, Chengalur-Smith, and Ballou, 2003), and data quality metadata (Shankaranarayanan and Even, 2006; Shankaranarayanan, Even, and Sussman, 2006). Research has shown that provision of quality metadata along with its associated information can result in different decision outcomes than when the decision is made using the relevant information alone (Dijkstra, 1999).

Providing awareness to decision makers of the options available, a decision space, enables fast visual comparisons in uncertain settings (Klein, Drury, and Pfaff, 2012). Chorley et al. (2012) present results from a web-based study that assessed the effect of Twitter metadata on decision makers. Decision makers calibrate their trust in a data source by reference to its agreement or disagreement with other sources of data, and with their own beliefs. Shankaranarayanan and Zhu (2012) examine how decision support systems can be designed to help decision makers benefit from data quality metadata. The problem for city model data can be processing and presenting 2- and 3-D metadata on the models. Showing indicators at a city scale is a challenge (Tourre et al., 2012).

Chorley et al.)2015) uncover insights on human behaviour in decision making for content selection. The additional presentation of data quality metadata potentially overloads decision makers, it may demand cognitive resources beyond their capacities. This, in the same way as other information overload, can adversely impact the decision outcomes. Moges et al. (2016) explored the impact of data quality metadata on decision outcomes, aiming to identify distinct groups of decision makers that could benefit from data quality metadata, and to study factors that promoted or were barriers to the metadata use. The output of this study is returned to towards the end of this chapter as part of the motivation for the thesis direction. Peng et al. (2019) employ visualisation as a technique to reduce cognitive load for decision makers in a spatial related setting. Similar results are found in research of metadata provision to decision makers (Shimizu et al., 1991; Romañach et al., 2014; Rožanec et al., 2022).

Shankaranarayanan and Zhu (2021) describe a prototype decision support system that takes advantage of a visual interface, then test its effectiveness in reduction of cognitive overload for decision makers using data quality metadata. Laird (2022) explores the role that metadata plays in memory retrieval and learning for decision makers. The classical models of decision making assume use of a single, constant strategy to reach decisions, or that decision making strategies as a process evolve slowly over time. Ashwood et al. (2022) suggest this isn't always correct.

Here it is worth reiterating the findings and useful model from Phillips-Wren and Adya (2020) and figure 2.2 (page 26) on the stressors for decision makers. Regarding uncertainty, greater levels of uncertainty in data lead to greater levels of stress and subsequent negative impacts on decision quality. As a result, the research suggests that decision aids and support systems can be designed to reduce the experience of stress and potentially increase the quality of decisions by mitigating the effects of data uncertainty on decision makers.

Uncertainty can be defined as an inadequate availability of knowledge about a situation that requires a decision. Phillips-Wren and Adya build on existing work on uncertainty as a precursor or contributing factor to decision maker stress (Schuler and Jackson, 1986). When combined with outcome risk in high value or impact scenarios, uncertainty is a clear contributor of stress associated with lack of knowledge about outcomes, the significance of any outcomes, and the lasting impact of them (Beehr and Bhagat, 1987). Organisations therefore, should have great interest in the handling of uncertainty for their decision making (Schuler and Jackson, 1986). Research considers the role of uncertainty in decision making in economic contexts (Meder, Le Lec, and Osman, 2013), while also finding the role of perceived uncertainty in the comprehensiveness of decision maker choices (Meissner and Wulf, 2014).

In the way information overload can be detrimental to decision making processes, uncertainty is recognised for similar effects on a decision maker's ability to process data in a decision situation (Simon, 1990; Landsbergen et al., 1997; Nutt, 1992). Uncertainty reduction approaches are associated with improved performances by decision makers (Field et al., 2006). In addition to stress already cited, uncertainty can create fear and indecisiveness for the data users (Covey, Merrill, and Merrill, 1995), and introduces bias in decision makers, interfering with their process (Hey, 1993). Uncertainty modifies the decision making deliberation or processing stage so that, under time pressure, only the most prominent dimension is likely to be processed (Busemeyer and Townsend, 1993). This is at the cost of other potentially useful dimensions of the decision, and decision makers may postpone action, lengthening the decision time, until more is known about the situation and uncertainty is reduced. This can result in reduced decision outcome quality (Pomerol, 2001). When unable to address the uncertainty in data, decision makers may employ expert judgement, whether theirs or that of someone else, and heuristics that simplify the decision space (Mahan et al., 1999). Hey, Lotito, and Maffioletti (2010) confirm the simplification behaviour of decision makers in uncertain situations. Time pressure and uncertainty for decision makers interact. The data processing strategy they employ and the task structure, the process they follow to reach a decision, is determined by the strength of the time pressure. When presented with an option of uncertain and reliable options, time pressure made decision makers more anxious and energetic, a state in which they demonstrated decision strategies to cope different to those with unrestricted time given (Maule, Hockey, and Bdzola, 2000).

When decision makers are unfamiliar with the data context, analysis by Price and Shanks (2011) shows that data quality tags such as metadata are associated with increased cognitive processing. This increased processing is in the earlier stages of the decision making process and delays generation of options and assessment of potential outcomes. This potential damage suggests a risk of introducing data quality metadata to decision makers in environments they don't have domain expertise in.

Decision making domains of high risk often fall under conditions of high time pressure and uncertain data. Decision makers can be assisted with decision support systems, and Sarter and Schroeder (2001) test the effectiveness of two different decision support systems. Inaccurate information, data of low quality, is costly. When inaccurate information was presented to decision makers performance dropped below baselines of the other study participants. Unless perfect reliability of the decision support system can be assumed, then interfaces using status displays are preferable to command displays as they allow more decision outcome performance benefits without the same vulnerabilities.

Visual representations of uncertainty can help people by reducing the processing to interpret the data. In investigating the effects of weather forecasting visualisations with both novices and experts, Nadav-Greenberg, Joslyn, and Taing (2008) determined the relative uncertainty in forecasts. The performance results for expertise levels were similar, and findings recommended an interactive display that offered a charted uncertainty in combination with expected values. A follow up study by the same researchers confirmed the enhancement of decision making in the weather forecasting context in the presentation of uncertainty data when communicating with non-expert data users (Nadav-Greenberg and Joslyn, 2009).

When designing decision support systems, it is important to take into account when the decisions are being guided by the visualisation of factors such as uncertainty and when they're being guided by the decision support system. Uncertainty should be presented continuously and not just at the point of decision (Griethe and Schumann, 2005). This is context dependent though. In research around air traffic operators that explored the effects of uncertainty visualisation on decision making processes, this is a high time pressure and high cognitive load situation for the decision makers. The findings suggested that the visibility of uncertainty data prompted the decision makers into worst case scenario approaches for their situation, which is safety critical (Riveiro et al., 2014).

Looking at interplay of decision maker experience and uncertainty, situation assessment time was longer for higher experience participants but time to select the course of action after reaching that state was lower. Under cases of high uncertainty, there was no difference in the times for taking course of action between low and high experienced participants (Kobus, Proctor, and Holste, 2001).

Considering the quality and uncertainty of spatial data, there are suggestions on how to make the data quality metadata available to decision makers at an appropriate level. Decision makers are gaining easier access to geospatial and place-related data but aren't necessarily equipped with any greater knowledge in the domain. This can be a barrier to the ability to assess the data quality and to incorporate that into their decision making effectively. Devillers et al. (2002) and Devillers et al. (2007) offer and implement a model and interface design that visualises data quality metadata for spatial data. Figure 2.4 shows the levels of the detail of data quality information that can be accessed and the visualisation of metadata at any level as an abstraction, a traffic light system for any of the dimensions of interest. The hierarchy of data quality indicators suggests how the interface can respond to decision maker domain expertise and also enables interactivity to decision makers to question the data further. Figure 2.5 shows how this is employed in the prototype interface.

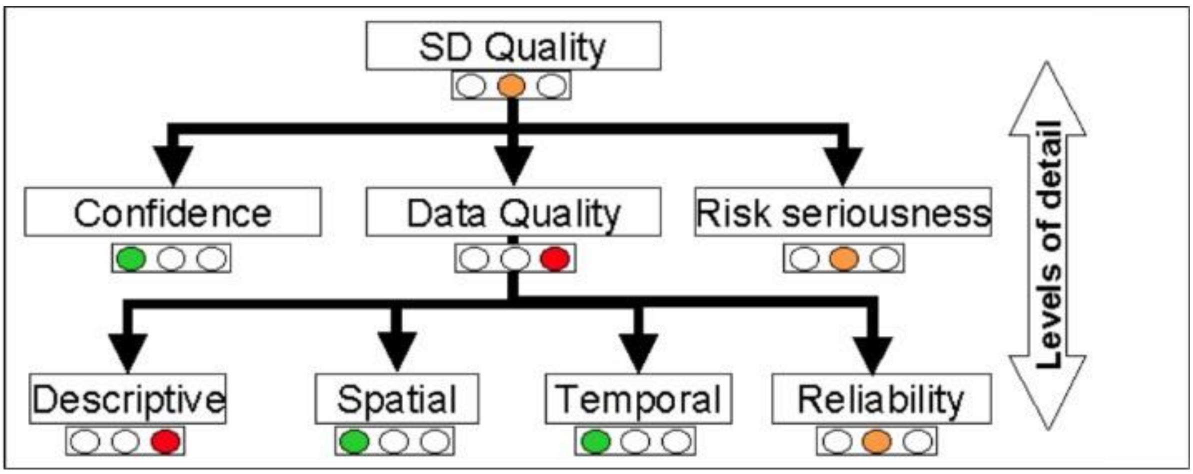


Figure 2.4 Conceptual Model of Data Quality Metadata Abstraction and Visualisation For Spatial Data Presented by Devillers et al. (2002)

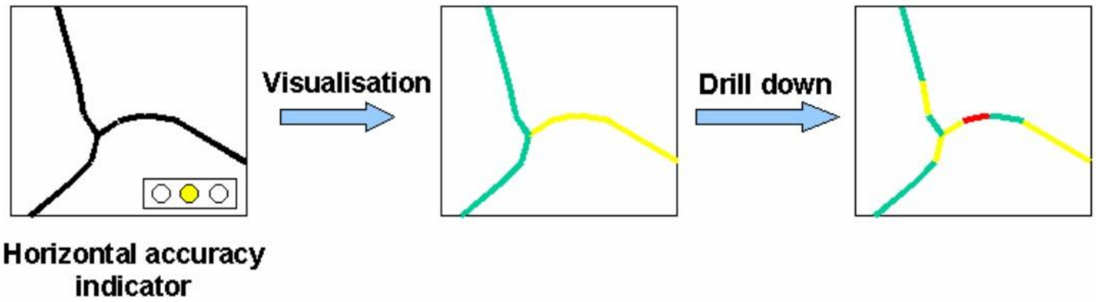


Figure 2.5 Example Application of Data Quality Metadata Visualisation In Decision Support Interface Presented by Devillers et al. (2002)

When the risk of poor quality data is high, impacts on decision quality could be mitigated with data quality metadata provision to decision makers. In a similar way to Devillers et al., a series of papers have explored the traffic light abstraction of data quality in place-related data visualised off the map. Figure 2.6 shows the way this was done by Watts, Shankaranarayanan, and Even (2009). The same model is used in the work this is based on and that follows from Shankaranarayanan and colleagues. This visualisation is an abstraction of information quality that can be measured along dimensions such as accuracy, completeness, timeliness and relevance. Decision makers can apply heuristics to this abstraction efficiently rather than more effortful cognitive processes to analyse, this means processing the data more easily, which should be beneficial in a time pressured situation.

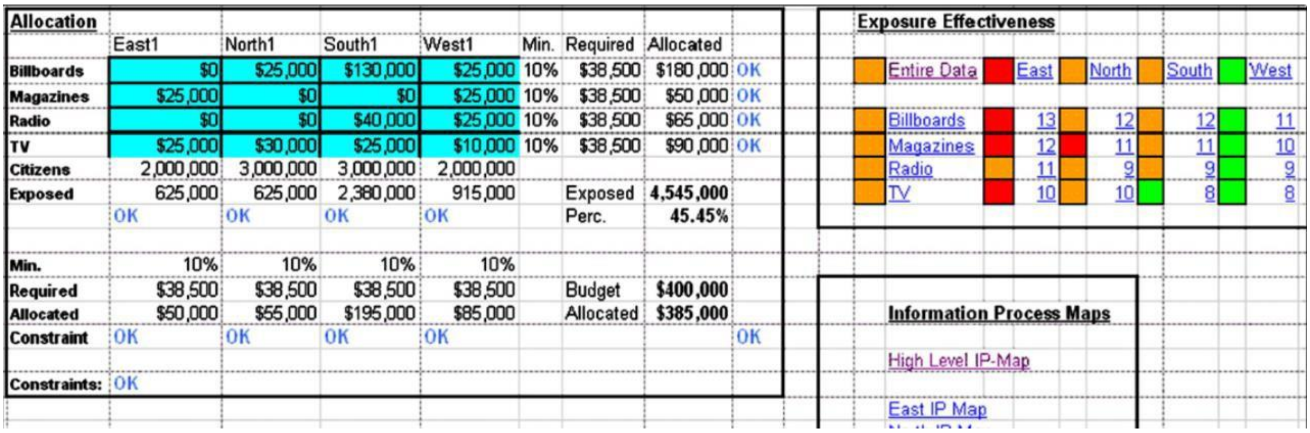


Figure 2.6 Example Application of Data Quality Metadata Visualisation In Decision Support Interface Presented by Watts et al. (2009)

There is good research into the effects of uncertainty, time pressure, and information overload on decision makers and decision outcomes. In solving one, issues can present themselves in the other dimensions. The work already highlighted by Philips-Wren and Adya underscores a need for the avoidance of information overload while tackling uncertainty in time pressured decision scenarios. All three are stressor factors for decision makers. Data quality metadata offers decision makers tools to interpret data quality to reduce some aspects of uncertainty, but this provision of further data that can overload them, or they may simply not have time or the expertise to translate it. Visualisations or simplifications of data quality metadata, indicators, abstractions such as traffic lights, or ratings on a scale, could speed up the accessing and use of data quality for decision makers, which could be beneficial in time scarce scenarios.

There is an opportunity for research to better understand the impacts of data quality metadata on the decision makers in their process of reaching decisions, and to validate in a different setting the effects of giving decision makers data quality metadata in formats they may more easily adopt.

Shankaranarayanan and Zhu (2021) and Devillers et al. (2007) motivate the use of visualising data quality metadata for decision makers with an easy to understand traffic light abstraction. These propose the interfaces and test the usefulness on reducing decision makers' cognitive loads when using data quality metadata, but can be combined with other research to explore what other impacts the visualisation has in the decision making context and its outcomes. In particular, the impacts when it effects the trust of decision makers in the data they're using. The research focuses on decision outcomes and process efficiency, with a gap to explore other elements of the process. Shankaranarayanan, Zhu, and Cai (2009) suggest the need for further work on the task efficiency effects, but also on the interaction of the data quality metadata presentation with the complexity of the task being carried out by the decision makers. The technique is beneficial in the contexts tested at this point, but further validation is of value, particularly identifying where the adoption isn't effective for the task.

Speier-Pero (2019) encourage the aggregation of data, in this case data quality metadata, in contexts of time pressure. Aggregating and visualising the metadata could be a way of transferring the findings on data aggregation to the data quality indicators that can help decision makers navigate uncertainty.

Returning to Moges et al. (2016), a comprehensive model of detailed data quality metadata effects on decision making is presented. This is shown in figure 2.7 and illustrates influencing factors in the adoption and use of data quality metadata, and the outcome factors considered in effects. This empirical study focused on outcomes of decisions and suggests an opportunity to further understand how the data quality metadata are used by decision makers in the process of reaching the outcomes. Data quality is demonstrated as an influencing factor in the decision outcomes, metadata can moderate this though potentially overloading, and is likely to show varying levels of benefits or drawbacks across different groups. The use of the information on data quality can be improved through training and education, increasing familiarity. Characteristics such as higher levels of data quality knowledge or domain experience are associated with more positive impacts of detailed-form data quality metadata, "decision makers who are familiar with the data have an intuitive knowledge about the data".

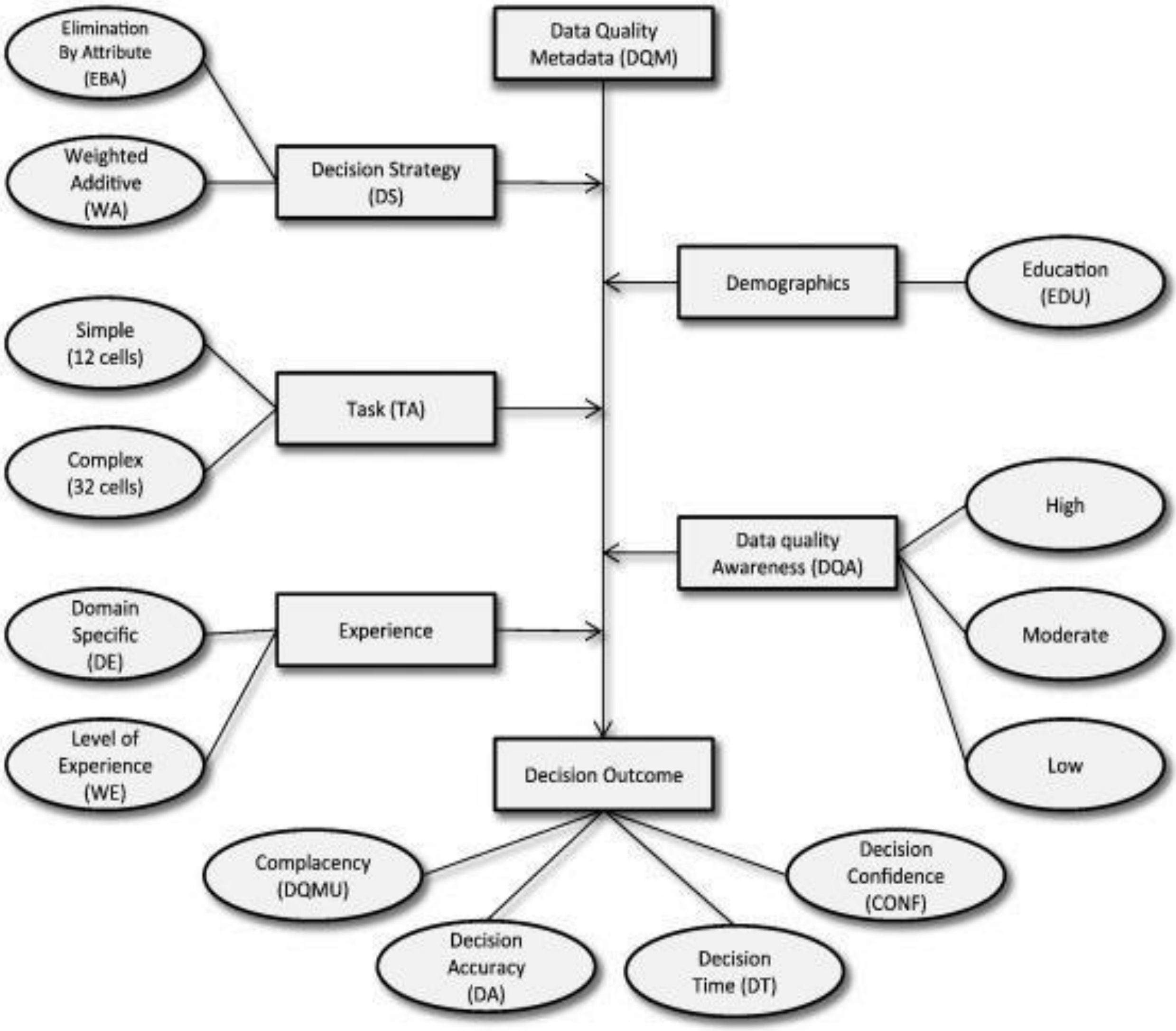


Figure 2.7 Model of Data Quality Metadata And Influencing Factors Of Decision Outcomes Presented By Moges et al. (2016)

For group decision settings and the use of decision support systems, it has to be expected that not all team members will have the same level of experience or familiarity with the data or domain. This exposes them to weaknesses which could be augmented under time pressure. Data quality measures such as accuracy, completeness, and timeliness could be aggregated to support these decision makers, and visualised to make it more accessible under time pressure. Time is mentioned in this work as a scarce resource, but not explored in any depth as to the effects of it on how efficiently decision makers of different expertise can assess data quality metadata. If the metadata can't be used efficiently by the decision makers to assess data quality and incorporate into their decision making process, then it is likely to be filtered and discarded in the way information generally is in avoidance of, or response to, overload. Reduction in efficiency may be acceptable if sufficient improvement of decision effectiveness or outcomes is expected, and time pressure is low enough. In addition to more explicitly exploring the relationship between time and the data quality metadata use, there is a need for more clarity on the role of uncertainty in the decision process for the decision makers. This can be a function of existing factors such as domain experience.

Giving quality measurements such as data quality metadata to decision makers should help them assess and incorporate the quality to their process, reducing uncertainty in the data and improving the trust as part of their decision making. An abstraction or simplification would make this accessible to non-domain experts, particularly under conditions of information overload or time pressure. Reduction in mental workload with visualisation of metadata is apparent, but what are the effects on other aspects of the decision making process for data users, factors such as their trust in the data or the decision outcomes under conditions such as varying time pressure? With the acknowledged growth and messiness of data available to strategic decision makers, it's a double-edged issue of introducing metadata. This is adding yet more data to the context but could help heuristics such as filtering on data quality to handle the quantity. There could be benefits to the trust in data-driven decisions but it needs to be usable under a range of conditions.

2.6 Summary

To summarise, the proliferation of technologies such as the Internet of Things has driven a growth in the collection, storage, and availability of data to decision makers. The growth of populations, shifting to urban centres, and the adoption of technologies is seeing a deployment of this data to inform the monitoring, control, and development of cities. These cities can provide lenses, examples of strategic decision making across a variety of groups in terms of their size, multidisciplinarity, structure, temporality, location, and other characteristics that influence the decision making. University campuses, as miniature cities, offer opportunities as test beds for developing and assessing technologies and policies.

Decision making, the activity of selecting from two or more alternative options, requires decision makers to be able to understand their decision space. They achieve a state of situational awareness that enables them to do this through a process of sensemaking, as individuals and as groups. When these decisions are data driven, decision makers need to be able to understand, assess, and incorporate the data effectively into this process. The ability to do this is influenced by factors such as information overload, time pressure on decisions, the complexity of the task, data quality, and uncertainty. The outcomes of a decision, performance of the decision makers, are also impacted by these. Decision strategies and heuristics are employed by decision makers based on aspects such as their experience, the decision support system, and task structure to address these challenges. For example, under time constraints and overload of information, decision makers will filter data based on relevancy to task completion to simplify the problem and achieve an outcome within the time available.

Data quality indicators, detailed or abstracted data quality metadata such as provenance, completeness, and accuracy, can function in this way for decision makers. Understanding is still needed on how visualisations of data quality metadata are incorporated under time pressures for group decision making, and how they affect aspects of the process such as the trust in the data they’re using, as well as the outcomes they achieve. With the prospect of growing and messy data in strategic decision making, the decision makers need to trust the data in inherently messy and overwhelming environments. This thesis will focus on growing the understanding of group decision making in context through an exploratory 1st study, before developing and testing an intervention in an experimental 2nd study.

3. A Case Study of Capital Project Management Groups

3.1 Introduction

As discussed in chapter 2, capital projects are significant long-term investments and can involve complex decisions when combining factors such as: budgets, the reasons for investment, the range of stakeholders, interdependent projects, and the impacts of construction and the product. Complex strategic decision making often requires management groups to be established involving stakeholder representatives, these teams are inherently multidisciplinary with the expected advantage of an increased knowledge pool. This study uses university campus capital projects as case studies for this type of management group. Project Management Groups (PMGs) are created at the university to deliver the project through to completion, and it is the representative members of two of these PMGs that the study will be conducting semi-structured interviews with. One of the buildings was an expansion to accommodate more collaborative academic work for a multiple-school research institute. The second building was a humanities-oriented teaching and student study space to meet a judged lack of space in the associated schools.

The university campus infrastructure and range of users means that decisions are made at differing levels of spatial granularity over a capital project. Spatial contexts introduce complexity to decision making in groups. In combination with this, the diversity of backgrounds and experience of team members means there is a need for clear focus and prioritisation of goals for projects. Some literature suggests that the human factors are woven into management factors in the decision making in successful project management (Cooke-Davies, 2002). This chapter explores the people as well as the data and decision making to try and understand how well the human dimensions are connected into the group operation.

Of particular interest in understanding complex spatial-related long-term decisions and the sensemaking processes is the trust in data and decisions for collaborating groups. There is a role of the larger institutional setting on individual projects, and it is also a factor in team decision making. In multidisciplinary team meetings there is an influence on discussions of the expertise of individual members during discussion, this can direct the mapping of roles and responsibilities of individuals in the team onto the decision making.

The chapter aims to further identify and present problems experienced in practical settings of these types of strategic team decision making. The study offers a case study of opportunities to support factors such as coordination in projects and consensus reaching in team decision making. To better understand the decision making process and how it relates to, depends on, and interacts with data, I performed an exploratory study. This study aims to understand the structure of the sensemaking and decision process for significant development projects on campuses, and the extent to which data are used to achieve this. In an effort to identify opportunities to intervene and support team sensemaking, the study investigates the following research question: “To what extent is data used in the group sensemaking and decision making process for significant development projects?”

3.2 Method

The ethics review procedure for the School of Computer Science at the University of Nottingham was followed and subsequently approved by the committee for this study (ID: CS-2019-R29).

3.2.1 Data Gathering Process

Participants were recruited from the PMGs of the two most recently completed buildings on the Nottingham University main campus to take part in semi-structured interviews. The semi-structured format was appropriate for the limited number of participants accessible for the interviews and would provide reliable and comparable data. This would enable interviews to follow a general guide of questions, while allowing for different paths that emerge from interviewees to be pursued in more depth. The goal of the interviews was to gain a qualitative understanding of the team members’ experiences and views from the projects.

6 interviewees (3 from one project, 2 from the second project, and 1 who sat on both PMGs) represented a varied set of roles at the university including heads of school, directors within the university senior management, and capital project managers. 2 participants were females, 4 were males.

Interviews were held virtually using Microsoft Teams meetings, and followed broadly 6 areas of questioning:

- An introduction to the participant to understand their role at the university outside of the PMG, the extent of their experience with capital projects, what they understood their role in this team to be, and whom/what they saw themselves representing.
- Framing of the project that was being discussed by summarising the purpose of the build as they understood it, this meant the driver(s) for the build, the target users, and some of the impacts and needs considered during the project.
- The wider working processes of the group such as the meeting frequency and format, the nature of discussions and decision-making involved in the project.
- The extent of data use by the team during discussions and the decision-making process, any data generated by the group during the project, and the format of presentation for either of these types of data.
- Further detail on the working method of the group, how they collaborated, tool use in discussions or presentations.
- A reflection on unforeseen challenges and their resolutions, desires from the participants if the project were repeated, and experience they carried forward to current/future projects.

Sample supporting documents were also sourced from the managing group of the PMGs, the University's Estates Office, these included terms of reference, and meeting agendas and reports for both projects represented in the study. These would be combined with written notes and the transcriptions from interviews for analysis.

3.2.2 Data Treatment/Pre-Processing

Written notes were collated from interviews that managed references to extra material such as PMG reports and the terms of reference. Interview transcriptions were anonymised, and unrelated sections were removed such as disruption from the interview during the call. These were then exported to Nvivo (Qualitative Data Analysis Software for Researchers | NVivo', n.d.) as the data corpus for thematic analysis.

Thematic analysis was carried out following a reflexive approach (Braun and Clarke, 2006). The first stage was in vivo coding, this was driven by the theoretical interest in the areas explored by the interview questioning, and by the initial research questions on how PMGs operate and how they could be supported. A list of initial codes was generated by a series of read-throughs of the interviews and familiarisation with the data, and emerging patterns were documented to begin developing themes for the second stage. The theme levels reflected the structure of the interview questioning, with overlaps appearing in responses being grouped into themes such as the discussion of data available and in the reflection of participant desires. These preliminary codes and themes then became subthemes to three emergent main themes, relevant to the research questions. A second stage of coding was then carried out, this time deductive coding using these emergent themes and subthemes from the inductive process. Allocating data to these defined themes generated a list of codes and relevant data extracts to be able to present.

3.3 Extracted themes

The 3 themes and the 12 subthemes generated by the analysis were:

- People:
    - Representation
    - Future occupants
    - Decision makers
    - Subgroups and related group
    - Gatekeepers and experts.

- Data:
  - Data types
  - Presentation and visualisation
  - Data flow
  - Trust/validity/veracity.
- Decision:
  - Decision flow
  - Granularity
  - Tools.

These cover the makeup of the PMGs and their degree of multi-disciplinarity, the extent of and opportunity for data use, and the nature of the discussion and decision making for these projects.

3.4 Theme 1 - People

Theme 1 explores the makeup of the management groups, whom/what these people represent, who is attached to the group, and what the roles of members are.

3.4.1 Representation

These teams are designed to be representative of the stakeholders for the capital project, and so the groups are inherently multidisciplinary. The degree of representation is determined through the managing group of University PMGs, the Estates Office, and the Chair of the group. This method using the experience of the Estates Office should capture most stakeholders, particularly the target end users of the building, but there is potential to miss representation of more removed or indirect stakeholders, such as campus visitors. One participant indicated that they joined the group for their building late because they hadn’t been invited to join even though it would house staff from their school and would physically

Connect to one of the other school buildings already in that part of campus. They put it down to a miscommunication, but that participant, and therefore that school, joined the group after they contacted the Chair and were brought onboard.

Some team members have a firm understanding from their own perspective of why they are part of the group:

> *P1: "…it has my staff in it, and it's connected to one of our other buildings."* and *"…my role was definitely to represent the school…bring forth any particular issues, of which there are quite a few that relate specifically to [us]."*

For one participant it was about what they were there to represent too:

> *P3: "I represent the students and the academics, and the university financially…I know how many academics need wheelchair space, I know how many have got childcare so have to work until 7 o'clock at night that sort of thing…So it's the data really, maybe I represent the data."*

Many members identified what they believe was a primary reason for their membership of the team, commonly that related to their job title at the university, though they also saw themselves as fulfilling an additional role alongside this:

> *P4: "I was there for two reasons, one to provide continuity…the idea was that there'd be a permanent member of staff to support the [Student Union] officer view, and the officer view would be the view of students or would be the representation of students…My view was more of a critical, operational, you know how are we going to do this, what are the impacts of this going to be."*

> *P5: "my involvement in the BDI project was twofold really, one was representing the IS (Information Services) infrastructure side of it, but also to look at okay that building came from having a really big ambition, and to make sure whatever that ambition was, it was translated into decision making around what was in the building."*

3.4.2 Future Occupants

The most directly involved groups can be very clearly seen for a project, often driving the lists used to pull together the management team members, these are the groups that all participants in the previous section identified themselves as representing.

However, the concept of future occupants or users, and the expectations of involvement can be disjointed within the team, or between the group and the stakeholders. One of the buildings was going to require a physical interface between the new build and an existing building. When considering the impact on those that would not be occupying the new build, participants often drew attention to awareness of how the building would fit into its place on the campus:

Neighbours of one of the new sites could also have had their deliveries impacted,

> *P1: "…there's some big limitations now on turning circles of trucks, so it's limited the size of trucks that can get to certain parts of that bit of the campus.", "…what does that mean for people, does that mean they have to have more deliveries…"*

A notable issue for both occupants and non-occupants was amenities. These buildings don't operate in isolation, they will either provide a service and will therefore draw non-occupants, or they don't, and the end-users will need to seek out amenities and services elsewhere, usually in nearby buildings:

> *P2: "…there needed to be greater consideration around what are these people going to do to eat when you suddenly parachute another 300, 400 people in."*

A particular issue highlighted in one of the projects was around cost implications for the new build and impacts for the future users. In one case the make-up of the future occupants and their activities could have large implications for VAT. For those not moving into that building there were cost implications for reconfiguring the old space that was being vacated to ensure it was suitable for them. Achieving this understanding of future occupancy and use can be difficult but significant in decision making:

> *P1: "…probably the biggest work in terms of the Project Management Group which then fed into the actual implementation group really is what the loading of people was going to look like, what the distribution was going to be between schools."*

P1: "…that would generate income through obviously having undergraduates there, so that was clearly teaching but what they hadn't realised that was undergraduate research projects from other schools would also take place in the building."

3.4.3 Decision makers

The flow of decision making and the way the teams work is explored in more detail in Theme 3, but here the extent to which the group are the decision makers in the project is considered.

In some instances, the group clearly act as the decision makers for the project, such as choosing the specification of the IT systems going into the buildings. As seen in the representation subtheme and in formation of the group membership, the managers of the team, the Estates Office, can act as the decision maker as opposed to the group. In discussing the decision on room sizes for one of the buildings, the Head of Estates at the time chose to increase the sizes to give some leeway for future class sizes. They did this based on their understanding of the current space usage for the buildings in this part of campus, and on university plans for increasing intake in the coming years for the relevant courses. They anticipated the courses this building would be supporting growing beyond the originally discussed room capacities.

There were several decisions highlighted that related to the running of the project, the build as a process, rather than the end product. The team were able to act with autonomy to shape this build process. For example, on choosing where to make space for contractors:

P1: "…there was an idea I had right at the very beginning which was to stick the builders into the underground car park because they were going to put lots of huts in front of the Boots building."

There were examples of decision influencers emerging in the group for topics that related to their role of representation or expertise, where the rest of the group may be non-experts and ratified a decision rather than making it. This will be explored further in the next subsection but Information Services presented an instance that they took on a role of decision influencers:

P1: "…that was one of the important decisions because that had knock on impacts to the trunking, you know whether its optical fibre, copper, whatever these are kind of very technical things but the decisions that were being made about the research led to impacts on the building…"

PMG members could be upskilled though to be able to act as decision makers alongside the experts:

P1: "…[there is a] complexity of the university and the regulatory environment that we need to operate in, so I've learned a lot more about the sort of specific building regulations, environmental impacts statements and policies, and how that drives some very significant decision making."

In one of the projects, future occupants were made decision makers, after their choice had been narrowed by contractors and the management group. The stakeholders had more direct involvement but through a curated list of colour schemes and branding options for the new building.

3.4.4 Subgroups and Related Groups

As seen in the previous subtheme, there are instances when decisions can be made or influenced by a stakeholder rather than by the group. This stakeholder was often part of a subgroup associated with the main representative team and would take on roles including fact-finding/justification projects, or were part of the wider planning structure of the university. The capital projects operated within a network of management teams at the university, meaning the group operated within meeting cycles of major university committees. The subgroups had a degree of autonomy when feeding into the main project group:

P1: "The biggest work, in terms of the project management group, which then fed into the actual implementation group really is what the loading of people was going to look like."

Participants acknowledged that these related subgroups were often used for decision making and then feeding back into the central group for ratifying decisions and discussions throughout the project:

> *P1: "I think that particular decision was probably done offline."*

> *P1: "I think that was done slightly outside of the PMG but it certainly was brought back to the PMG to be kind of discussed and noted."*

This overlapping of subgroups can cause some participants to struggle to separate the roles and the activity, and the purpose of the management group:

> *P4: "What you found was there were a lot of meetings outside of meetings…certainly there were separate meetings about specific topics but all the big items were discussed in PMG."*

> *P1: "I've got to be sure it definitely happened at PMG and didn't take place somewhere else."*

In the instances that these offline decisions are made by subgroups it is unclear to what extent the team could then scrutinise the decisions in their role of ratifying them.

3.4.5 Gatekeepers & Experts

In their roles as representatives of a stakeholder group, many of the participants were to an extent an expert in an area of discussion for the project. Some of the team members acted in the capacity of a gatekeeper to data or to access a user group. The group managers, the Estates Office, were one of two notable groups whose representative was a significant expert and gatekeeper for discussions. Sitting between the university, contractors, and consultants the Estates Office recognise themselves as the conduit, experts and gatekeepers:

> *P6: "…arguably we're the ones who have more knowledge across the whole project if you like."*

> *P6: "…not an overseeing role but a sort of making sure the right information is getting at the right times to the group."*

The other notable related group was the university Finance committee:

> *P1: "All these PMGs have a representative from Finance…they'll basically say look you can't do that, or you won't be able to do that or this will need approval, that's their job."*

Participants recognised that experts were also involved from future occupant groups for reasons such as understanding of health and safety zones. In some cases, the members recognised themselves as the experts or gatekeepers to help the team understand detail of how much teaching would take place in a building or space on campus, or evidencing the need for single occupancy offices:

> *P3: "I lead the team who build all the timetables for the university and who run all the exams for the university…I know and I can get the data for what areas of campus are going to be busy with what sized groups."*

3.4.6 Theme Summary

This theme highlights the varied makeup of the teams, multidisciplined representatives of many stakeholders in these two projects. The exact membership of this group is determined through appointment of a Chair by the university Estates Office and generation of a list of representatives by the Terms of Reference. This process generates only an initial list of stakeholders, and it is clear as projects develop and are modified the list changes as true stakeholders that were unaccounted for emerge. The interviews revealed a strong connectedness of campus user groups and interdependencies between the future occupants of new building projects and the extended list of other stakeholders. It was common for participants to describe how different groups would be interested in not just the new space that was coming but also the space being vacated, and the space vacated by those that take that space up, and so on. This created significant interdependencies when considering ramifications of decisions about the new space.

The collaborative setting demonstrates well the connectedness of a population in space and its use. There is a spatial relationship between these campus users, their buildings, and users beyond just occupants such as campus visitors and deliveries. They interact with each other either intentionally or not. This is highlighted and will be discussed in the decision flow subtheme, but the connectedness can be demonstrated by the amenity discussions. These buildings don't operate in isolation, they will either provide a service and will therefore draw non-occupants, or they don't, and the occupants will need to seek out amenities and services elsewhere, usually in nearby buildings. Introducing a new building, rather than redeveloping an existing one, certainly increases the number of people that will be in that space on campus. This increase needs to be considered with the capacity of that part of the campus, or wider, whether that is amenities, or related to travel such as parking options, bike spaces, and accessibility.

Needs for, and impacts on, future occupants and non-occupants should be covered through a combination of representation directly in the team, involvement in subgroups and related groups, and through experts in the group. The extent of offline decision-making or conversations described by participants suggests that this representation isn't ideal, stemming potentially from the identification-of-stakeholders stage. These offline discussions can be concerning for the team responsible for delivering a project, they need to be able to scrutinise and understand decisions that have been made on their behalf or outside of the group. This could be most challenging in the case of indirect stakeholders, where a user group that's ultimately not going to use the building will be impacted by project decisions. An example is the space that is expected to be vacated as a result of the project and how that will be used. The end users of this vacated space have a keen interest in the decisions made about the new space because one influences the other. There was evidence of missing input from a future occupant group in one of the projects, a participant indicated no one seemed to have spoken to the performing arts group about their needs for one of the spaces being designed. This demonstrated an issue in the identification of stakeholders and the measures taken to gather their input on requirements for the project.

The roles assumed by team members are fluid during a project. The multidisciplinary nature of the groups means individual members change their role within the same project depending on the demands of the group. They can take on the role of expert in the area they represent or be a gatekeeper to data for use in discussions. They could be brought on as a future occupant, but then act as a representative for a related group of non-future occupants because of their role at the university. Members can be tasked with data/fact finding for discussions as a sensemaking step to the group decision making. These mixed perspectives offer a challenge in how individual members and the group can scrutinise decisions in their role of ratifying them, or in exploring data to arrive at a decision when they have the autonomy to make one. Through sensemaking using relevant data, members could be upskilled sufficiently to act as decision makers alongside those that were initially described as experts. For certain topics of discussion and decisions being made, some members moved into a role as a decision influencer, trying to steer discussion of the group ultimately to a particular decision point. This behaviour was most often seen where the discussion was most closely linked to a role a team member initially identified in the interview as their purpose in the group.

This theme reveals in many respects that the PMG acts as a central hub for the stakeholders in a project and can be a well situated mechanism for discussing and deciding on aspects of capital projects at the University, bringing together stakeholder needs and perspectives in assessing decisions. The varied makeup of the PMG in this context is its strength, it is necessary for them to function in the representation, coordination, and input of the stakeholders that are involved with building projects on the campus. These groups are inherently varied therefore in the levels of experience members have with using and interpreting different sources of data, and this is a challenge in supporting them. Experts in one domain aren’t necessarily experts in all the data and domains encountered in developing and constructing new buildings.

3.5 Theme 2 – Data

Theme 2 explores the extent to which data are currently used by PMGs during a project and opportunities for further use of data. It also looks at some characteristics of the data that are used such as ownership and the trust in the data, and how it is presented.

3.5.1 Data Types

Across the projects it was apparent that data are used in the discussions and decision process, many of the same types of data are used across different builds. The most prevalent types align with the role of the management group and the nature of the buildings that each group was tasked with.

All participants indicated the extent to which the future occupant data were used in their decision making. This is expected as they are tasked with a building project to meet a need for a set of people, and the quantity and composition of the occupants would influence the solution that meets that need. The source of this data and the granularity of it varied. For one of the buildings the need being met by the project was focused on teaching space and capacities, this meant that a significant source of data used was the university timetable data. This data source was able to provide indications of the current situation on the campus, detail on the people, and the spaces they would be using, and led to decisions such as class sizes needed:

> *P3: "…the data for what areas of campus are going to be busy with what sized groups, how popular, you know what size lecture theatres, what size seminar groups, how many how busy places are going to be, how many labs they've got that sort of thing."*

> *P3: "…we had lots of data on space usage…Yeah its class sizes and things like the percentage of, what I did was the amount of classes that I had to send to other areas of campus…And the amount of time waste walking backwards and forwards."*

The timetable and future occupant data brought with it a spatial component, demonstrating some of the ways that the team could consider the project as part of a wider picture of the university campus, or in one case the city-scale situation for the university. Mentioned by nearly all participants was the amount of car parking before and after the builds, including the detail of different types of parking space that would be available. Similar to the data above, the car parking was often discussed in a spatial nature, relating the spaces that would be available to nearby buildings and landmarks. Here there is an indication of related metadata to car parking, the walking distance from target buildings. This was not explicitly captured but indicated a further spatial element to the data type that was considered by some team members.

In discussing cars both groups also covered flow of traffic in the nearby area of campus and the impact of the new building and the construction on that traffic. Traffic flow of pedestrians was also covered by all participants. This will be explored in sub-sections to follow, but data weren't used explicitly in either of these scenarios where the team discussed potential impacts of the build or the post-completion effects. These present a clear opportunity for collection and use of data to show the current situation and augment discussions on impacts.

The combination of vehicle traffic, car parking, and pedestrian flow combined for one participant and their concern for modalities of transport and the impacts of the build. This example will be returned to in section 3 discussing decision flow,

> *P2: "…if that is well we're gonna reduce the amount of parking space but increase the headcount and people will just have to use other transport approaches."*

But they weren't convinced that sufficient alternative modalities existed or at least weren't supported properly for the number of people they were expecting to introduce to the area with the new build. On talking about pedestrian flow, two participants indicated a more abstract element to the pedestrian data and its spatial component, this was the idea of pleasantness of walkways and environmental data such as noise levels and greenery.

The building process itself also highlighted data usage: underground service plans, furnishing and equipment mapping, project cost and project time. Each of these projects is assigned a budget and has constantly updated costs for the build, which each decision could impact. Equally each project has a schedule for delivery and milestones, with impacts for each decision.

3.5.2 Presentation and Visualisation

This theme highlights the ways data are presented to the group for discussion, and may demonstrate how the data that isn't collected or used could be incorporated.

The most common tool for sharing data with the group was written reports, circulated ahead of every meeting, these were used particularly for the operational data highlighted in the previous subsection (time and cost). With these reports came more detailed data relevant to the discussion and decisions for that scheduled meeting in an addendum of papers, with the headlines pulled into the main report. This addendum often included papers put together by the members such as evidence for the use of single-occupancy offices or the timetable situation for future occupants.

Maps and building plans were presented to the group to aid discussions and to highlight some of the data being used. The maps were mostly restricted to service plans and construction impacts, while the floorplans would be used to highlight detail throughout the building. Maps and floorplans didn't mean many data were being presented to the team, participants described that pedestrian and traffic flow would be highlighted with a couple of arrows of different sizes.

In terms of tools to present any data in the meetings, the circulated report displayed on a screen was used along with PowerPoint presentations to guide discussion and decisions:

> *P1: "There was presentations, we used Teams, so there was a Teams so everything was accessible so to be honest people were there with their laptops or iPads or whatever they were going through the documents live, there would be reports, I mean just the typical presentation either a pdf or a PowerPoint."*

> *P4: "We'd normally put the PMG report up on the screen as well in that room, just to make sure people could look at it and actually focus people onto particular elements."*

3.5.3 Data Flow

Considering the data that were available to the teams, and the ways they were presented, this section looks at where the data that were used came from, such as instances of when team members would need to provide the data.

The university and project leads, the contractors and Estates Office, were owners of data related directly to construction such as building plans and underground services. The management group as a collective generated data that was used in their discussions, this was centered mainly on the future building occupants and use. Individual members of the PMG also acted as sources of data, tasked by the group or Chair to provide some data as evidence for use in decision making from their position as an expert or representing future occupants:

> *P1: "I was asked for some evidence…I provided how much teaching time would take place."*

The meeting reports were often a main source of data flow into the group:

> *P4: "…what you got was an update on progress, you got an update on the finances every, you got a risk assessment to go through, a key milestones, a standard I would say a standard project report which is basically updated the group on the decisions that had been made, the actions that had been taken and any decision that was requiring the groups input."*

There was significant flow through the group as the team communicated outwardly to the stakeholders and to related university committees they operated within:

> *P1: "I can remember quite a lot of discussions about when meeting dates were and how it was important to get this data to that group."*

3.5.4 Trust/Validity/Veracity

With this understanding of the types of data that are used, this section now asks to what extent members trust the data in their discussions, if they can scrutinise one of the pieces of evidence presented for a decision made.

After one participant acknowledged most data were fed into the group, it wasn't clear whether it was always accepted at face value or challenged. A different participant described how this attitude may have changed over time depending on the source of data:

> *P3: "I think when I came in the faith in timetabling was quite low at the university…people didn't understand timetable data back then, people didn't want timetabling data back then, but now our data is in such a good state that we're actually using our data as a source of truth for things like campus solutions."*

The range of accuracy of data available to the group was exhibited by two examples of specific technical data from the earlier and later construction phases on the same project:

> *P1: "The university no longer has accurate plans of the services, underground services."*

> *P2: "…we were then able to have technical teams go through literally room by room workout where every single power socket would go, internet socket, every item of equipment was mapped out in place and so the level of detail was phenomenal."*

There was a desire to be able to challenge presented data more, particularly where it had been used to justify a decision:

> *P4: "I think what would be useful in all projects is to test the validity of assertions, particularly around space usage…there's a theoretical usage and an actual usage."*

Though PMG members were able to acknowledge that the data weren't always valid, there were mixed responses on how that was dealt with, and how the data could be questioned. The issue of the underground services data highlighted above was remedied through several ground surveys to provide accurate data. This time to remedy inaccurate data wasn't always available. Space usage and occupancy illustrate the interaction of provenance and veracity of data being used in the team decision making. This is a data type being used for evidence in decision making but participants disagreed on whether it was accurate data being used, and their levels of trust in the data used and the conclusions varied:

> *P3: "…yeah I'm surprised that I've not been asked to review it…But I'm guessing that if the space utilisation technology that we put in is working correctly then I wouldn't need to, so maybe they're getting it from there."*

> *P6: "…the occupancy levels aren't great and what we installed in Teaching and Learning Building was a sort of infrared room checking device or whatever it is, apparently it doesn't work so well."*

A contradiction for some participants was particularly apparent discussing the accuracy of their data and how much it could be trusted in sensemaking or as evidence for decisions. Combined with the occupancy technology above, one PMG member explained:

> *P3: "I can get the data for what areas of campus are going to be busy with what sized groups, how popular, you know what size lecture theatres what size seminar groups, how many how busy places are going to be, how many labs they've got that sort of thing"*

While two described how and why there is a lack of trust in that type of data used:

> *P4: "…we did a quick and dirty usage analysis a couple of summers ago round that and we reckon that no more than 50% of the rooms that were being booked were actually being used."*

> *P3: "…of teaching bookings probably about 70% were being used and the meeting room bookings, about 50% were being used…Now that's a massive waste of space when I'm saying look at all these bookings we need new buildings."*

People movement both inside and outside buildings was another type of data that most participants agreed had a degree of fuzziness to it, and therefore they questioned the validity of a diagram showing predicted flow:

> *P2: "…if you try and get from say the security station that or the cut through to the Pharmacy building up the road towards Trent and so on, if you try and get from there down to the QMC bridge there are so many different ways you can walk."*

> *P3:"People don't understand that you're in a lecture theatre of 300 people and 300 people could go 300 different ways."*

3.5.5 Theme Summary

This theme has shown that there is a large range of data types that can be used by these management groups, and the availability to them is limited in some cases. There are staple data types that are common across these capital projects. For the operation of the group these include: the timing of the meetings, related committee schedules, build progress and forecasts, and financial data for the build as both an isolated project and as part of the larger university structure and budget.

Future occupant groups and numbers, transport modalities and car parking people flow in and around these buildings featured in discussion from all participants, but with disagreements. It was not consistent across or within projects the extent to which data present was questioned, whether valid data were driving a discussion, and the extent to which they trusted the data or the conclusions.

As a data type in decision making, future occupants featured heavily in exercises of group members to provide numbers. The final occupants are negotiated throughout the project and so it must be questioned how much these figures at each stage of the project can be relied on or how uncertainty can be managed. This highlights some issues in: the data gathering exercise; the scrutiny of the future occupant data claims when presented; and how well the delivery of the project aligns with the planned occupancy. Consideration needs to be put into how team members can build trust in an important sensemaking data source if their experience is preventing them from trusting it.

Both projects presented scenarios where there was a question about the trust in how or where the data had been generated, and the veracity of it for use in discussions. This trust could be influenced by metadata such as the provenance, commonly it was guided by the individual’s experience at the university. Most of the data are not interactable for the group. The presentation method and flow of the data made it difficult for a member to interrogate the data or test any assumptions. For some of the participants this may have been acknowledging the fuzziness of the data type. There was a desire to be able to test assertions either with data or assertions being made of the data.

Timetabled occupancy data presented a case for expectation versus reality and the validity of data in sensemaking and data-driven decisions. One participant described how it is being used as a source of truth but there is disagreement between at least 4 participants as to if that is valid data. Historic room surveys demonstrated 30-50% error on room usage against what was booked. Participants also agreed that, for example, a timetabled room for 100 people often is not filled with 100 people, at least not for every session it is timetabled over a term or year. If there is this mixed level of trust in the veracity of some data, what is the impact on the team sensemaking, and on the decisions that are made?

Looking at the discussions around space usage, there was evidence of requirements using two different sources, timetables or installed sensors, that differed. These conflicting multiple sources demonstrate an opportunity for use of metadata, namely around provenance in this case, to allow team members to establish data quality and negotiate the truth as part of their sensemaking discussion.

Cost presented two types of data that could interact. The forms of cost included in the meetings covered both historic and predicted type data. This parallel of forecasted project costs/budgets and eventual spend could reveal useful data by tracking with the project timeline to identify significant deviations from prediction to reality. This could then feed back into the project or into subsequent capital projects on the campus.

There is a clear opportunity for introduction of grounded traffic and pedestrian flow data, it connects into the modality of transport. These are not just projects on the inside of a building, but the building in situ, embedded in its surroundings, the rest of campus and communities beyond such as commuting occupants and visitors.

This case study demonstrates a setting where data are brought into the space in an unsophisticated way. Ad hoc reports and requests for data leave the decision makers in a mostly reactive state potentially short of a full picture. This environment demands and relies on a greater influence or use of opinions and individual experience to make decisions than on data driven discussion. The data that is presented is highly varied in granularity, temporality, and degree of structure. It's messy. The understanding of the data, and its implications in the decisions being made, is influenced by the perspectives of the different PMG members. The groups aren't equipped with all the data to challenge or assess the assertions of the group in the way that they want, or with the metadata to help assess the validity of the data they are using. When uncertainty in the data or assertions of data is raised, the groups have to negotiate based on their roles and experience how to proceed and to what extent they can depend on the data.

3.6 Theme 3 - Decision

The third theme investigates the project management groups as decision making units. This considers the nature of the decisions that are made by the group, those that are made for the group, the granularity of these decisions, and the tools used to aid decision making.

3.6.1 Decision Flow

The PMG as a body sits among subgroups and wider university governance, and as with data, there is a degree of flow of decisions into and out of the group. They are not the single decision-making body on a capital project but have the capacity to make a number of decisions during the process. These projects are created within the Estates Office and with university senior management to address one or more issues. Work is done by groups external to the PMG before one is formed, with a problem identified and proposed solution pulled together by the capital project team within Estates Office and some other stakeholders:

> *P6: "We went through all the committees last year with a business case and presented it, and eventually we got to Estates and said right we're at a stage, we want to progress it further, we need a PMG convening."*

Responses did demonstrate that the team had the capacity to make decisions and influence change in decisions that were made earlier in the project or before the group was assembled. This was often driven by presenting evidence compared to an original case put forward:

> *P3: "The lecture theatre was originally planned to be a size 120 interactive lecture theatre and we looked at interactive lecture theatres and thought they're brilliant however there is no need for a size 120 within the area."*

Within meetings the Estates Office representative would often highlight the potential impact of decisions the team could make, both on the building program and the larger strategy at the university for its capital projects:

> *P6: "…there's a lot of attention to that part of it, the program and how, if we make this decision what impact is it going to have on the program."*

As with the data involved in the discussions, many of the decisions had their flow dictated by other more permanent groups within the university governance structure. The team may make a decision, but it could need approval, and therefore evidencing.

In terms of how decisions were arrived at, the Chair of the group mostly led a discussion around the issue for contributions and questions from group members until there was sufficient agreement. The discussions would be a sensemaking exercise for the team to understand the issue being addressed and the solution(s) being assessed, then work towards consensus through presenting data and papers in the reports, and discussion in the room.

3.6.2 Granularity

There is a range of granularity of decisions that the group can make on what the building looks like, the feel of it, and how it would work fundamentally. Even if the decisions in isolation are specific, it was demonstrated that the group does have to consider the project program and the broader strategy for the university, and the impacts of decisions on these. The decisions made at the most granular level could cover exact space use and equipment, both in and around the site:

> *P4: "…not just that so for example do you want tablet-top tables in your lectures theatres, for example do you want how many left hand and right hand ones do you need, because of how many students are left handed and how many students are right handed…And if a left handed student gets a right handed one will it compromise them or will they complain, you know those sorts of conversations you get into quite granular detail."*

Stepping back from exact furnishings in rooms, the groups did determine the usage of the rooms and the way this would influence the users:

> *P5: "…so the discussions around that were about not just the physical layout of the building but how can we naturally make it easier for people to have those accidental conversations."*

At the broader level, the big items as described by participants were decisions that had the biggest impacts on the project and the implications of those decisions:

> *P1: "The biggest issues we dealt with were things like the tax which was a big thing because that was a you know a million pound plus decision and the bridge had to be built very long between the two bits of CBS BDI, planning permission and things were complicated."*

> *P1: "…shown certainly at some point early on how the general philosophy of the university's campus plan was consistent with what they were doing, so there's long term plans for that portion of the campus."*

Most concerns regarding decisions being made by the group were focused on the immediate surroundings of the building, the neighbouring buildings. Participants indicated the group did not always achieve the right considerations across the levels of detail for decisions made, that could affect both future and non-future occupants, such as the environmental factors and the student experience of the building. Influencing the granularity of decisions was the frequency of meetings, on average once every 2-3 months. There were disagreements between members on recalling the frequency, and this may relate to the fuzziness of the groups and their subgroups and related committees.

3.6.3 Tools

This final subsection explores the extent to which tools are being used by the teams as part of the decision-making, and indications of desire to use tools to support their discussions and decision-making process.

Bringing forward the methods of data presentation, participants portrayed the reports and presentations as tools, both as sources of evidence for decisions and steering for discussions in that meeting. One participant highlighted their use of a vision document as a tool for the group to assist in the conversations about the space use in the project, it summarised what they understood the identified problem and project as the solution to be. Maps were used across both projects, presenting to the group members, and in one project as part of the discussion on pedestrian flow in the area with decisions being made based on that.

It was apparent that some forms of data were used as a tool for the team decision making. These included the timing and financial data when considering impacts of decisions on remaining project schedule or budget, and often when covering issues on space occupancy:

> *P6: "That's a fundamental thing of any decision we make so we have to make sure that if we're say, if we say to the PMG you can have pink carpets, but it's going to add 3 months to the program they need to know about that before they make the decision…same for costs, if you want pink carpets it's gonna be half a million pounds extra."*

Across all participants there was a clear desire for more data as a tool for decision making in the group:

> *P4: "What I would have liked was the ability to challenge, with data, saying okay well this building is intending to provide X number of rooms totaling this capacity, what's our evidence that we need this and that were not just inefficiently using our spaces at the moment."*

One of the participants also stressed use of tools to better engage the stakeholders, communicating decisions made as well as making them:

> *P1: "This group had a website…there was lots of communications, so good communications, particularly in projects like this impact upon lots of different people."*

One representative showed a desire for a more in-depth reflective post-occupancy evaluation as a tool, enabling predicted data used in one project to be validated and able to inform future projects using the same or similar data sources.

3.6.4 Theme Summary

This theme highlighted the variation in perceptions of the management groups in their purpose and operation, and a number of opportunities to support the groups in carrying out the decision making task as part of a broader strategy.

There was inconsistency in the understanding of which decisions are made for the team thatthey operate to ratify, which they are able to make with a degree of autonomy, and which decisions they can make that will also need to be passed to subsequent groups for approval. For the decisions that were made outside of the team there was an appreciation for the role of subgroups, future occupants and experts being given more control over the process, but it was ambiguous for some members as to the role that left them with, or how the decision fitted with a strategy they may not be aware of. When carrying out the task of ratifying these premade decisions, the groups had in some cases challenged with evidenced arguments and altered the decision for the project, but would have liked to scrutinise more of them.

This interdependency of operating groups within the university structure means that although a capital project may take a number of years to complete, there is a low degree of pressure put onto the decision making for the teams to maintain the pace for other committees or boards.

Some of the most granular decisions such as furnishings were made with the most autonomy as a group, with use of financial and construction program data of the project to understand the ramifications for decisions. The largest decisions that were made by the group involved the most interaction with related groups and an extended series of approval. These showed a much broader consideration for the strategy of the university, the motivation for the project, and the building in relation to its locality on the campus.

Whether or not the group was operating as a decision-making body or in ratifying a decision made for them, it was clear that there is an opportunity for greater use of data as a tool to enhance the team sensemaking process, to understand fully the issue they are resolving and the decision they make. Through this data driven decision-making they could also enable better assessment of assertions, and approval or recommendations for change, and eventually communication of the decisions.

Whether the group was making a decision or ratifying one, they commonly had to start by undergoing a team sensemaking process to understand the situation and demands, to be able to appropriately act. This is continuous throughout the project as it develops. It is important that the team members know the problem(s) being solved by a capital project, as it forms a significant driver in decision making and is a frame for goal-oriented sensemaking. Given the length of these complex projects, it would assist joining team members to have a common basic framing of the identified problem and initial proposed solution. The vision document described by one participant presents an interesting sensemaking tool as a shared review of the “current” situation.

Participants highlighted multiple times the desire to challenge decisions or assertions with data, as an example, wanting a clearer view of the future occupants. This points back to the need for accurate data. In the cases of asserted and eventual occupants of one build, and on student timetabling or space monitoring technology, participants demonstrated a skepticism around some data sources. For different reasons, some participants did not think the data they were using was accurate, therefore they did not trust it and did not have full confidence in the decisions made using those sources. There is a challenge then to provide data as a tool to these groups to enable the team sensemaking and decision making while engendering trust in that data and subsequently the decisions.

These meetings have some tools (tablets and laptops) already available that could be used differently. Currently used to follow reports and agendas, they could also have access to interactive data, exploring as a team but also individually to interrogate before making a decision.

The teams didn't function through voting on decisions, instead they moved discussions towards a shared consensus to make a decision. This suggests a greater degree of shared sensemaking is required rather than the case of a group voting approval of decisions. In the voting scenario, individual members could reach their own conclusions on seeing papers/data presented, make their decision, and cast a vote. However, a Chair aiming for group consensus requires more explicitly shared understanding and discussion. This discursive process to reach consensus may also lend itself to being more iterative and encourage scrutiny of assumptions or assertions.

This consensus reaching process in a setting of limited or variable data availability exposes the decision making to be influenced more by strength of voice and levels of individuals' perceived experience in the relevant domain. There is an opportunity to support better or more equitable decision making with an intervention of improved data presentation, including metadata. This intervention could support greater evaluation of assertions in and of data. Additionally, an intervention could encourage and facilitate more structured use of data in the process. A more reliable and consistent understanding across the diverse group of stakeholders could be supported in the sensemaking process.

3.7 Cross-theme Summary

There was a theme across the participants of a discrepancy between the expected or reported and the reality, such as timetable data for generating requirements and surveys of booked room usage in existing meetings. With this difference in claimed or assumed needs and evidence or knowledge of a different reality there is a degree of trust lost in the data used and the decision made. These assertions can be, and in some cases were, questioned by individuals and discussions followed around this with the experts and other PMG members.

The operation of the team seemed most smooth when the flow of decisions and members involved matched the granularity of the discussion, properly representing future occupants and considering the implications on the neighbouring area and the longer-term strategy.

The acceptance and interpretation of assertions and any information presented varied across experts and non-experts in the areas. Certain roles, if they were tasked with evidence gathering in a report or were respective experts on the topic, were the gatekeepers for different decisions and data. Each member had their own perspective of the role of the project that was shaped by their experience with other projects, their role outside of the group within the university, and their awareness of concurrent projects and wider strategies for the campus.

The discussions about future occupants for a building highlight a number of shared issues in the themes. Groups did not want to know the name of every researcher or student that would be moving into or using the building, though they wanted to know the future occupants to build for. Research groups fluctuate in size, occupancy levels for lectures and booked rooms were up to 50% wrong, and attendance at lectures isn’t the same as the timetabled capacity of a module. These future occupant numbers were incorporated into the collaborative sensemaking and decision making on room sizes, equipment, and impacts on the surrounding area with pedestrian flow, transport modalities and amenity needs. This highlights some issues in: the data gathering exercise; the scrutiny of the future occupant data claims when presented; and how well the delivery of the project aligns with the planned occupancy. Consideration needs to be put into how team members can build trust in an important sensemaking data source if their experience is preventing them from trusting it.

These findings point to a need to better support the structured incorporation of data and metadata into this group decision making. With better shared access to data, the members, from their range of perspectives and motivations, could make and discuss more evidence-based proposals. Importantly, with the inclusion of metadata, members of the group would be able to question the quality of that evidence, to challenge and assess the appropriateness and validity of that data driving a decision. As a group this could increase the trust in the data that is adopted, and the confidence in the decisions and actions at which they arrive in the process.

3.8 Reflections

These capital projects and their management groups offer significant opportunities for greater data usage in a team sensemaking and decision-making environment. With respect to the initial research question on their operation and the extent to which data are used, there were a few key findings.

In cases where data were made available to the group, there were commonly issues with what was available, issues of accuracy highlighted by future occupant lists changing throughout the project that were incorrect still at the point of staff and students moving into the building. In many cases there was a desire for data from participants to enable them to test assertions or decisions being made.

In most examples reported by the participants the data used in discussions and arriving at a decision were not interactable. The presentation and visualisation methods made it difficult to interrogate the data or test any assumptions, and this contributed to some ambiguity for members as to the purpose of the PMG and the decisions it was able to take during the project. Though some tools for interacting with data were available in meetings such as the tablets being used to follow the reports, consideration should be given for this interaction by individuals and the team impact on the collaborative sensemaking process.

One of the projects demonstrated that ambiguity in data impacted the decision-making process, reducing the confidence or satisfaction in the final decision. This asks the question of how transparency with the fuzziness or the veracity of data can change the confidence in assertions from the data or decisions reached? There is potential from enabling deeper questioning of assumptions and data for individuals and the team to increase satisfaction in decisions made.

Trust can be engendered in data sources used during the sensemaking process. From the examples of student occupancy and timetabling in the interviews, this trust could be engendered through provision of metadata, highlighting characteristics such as provenance and allowing the individuals to make assessments of the data quality. What then would be the impact on the confidence of individuals and the team making these decisions and communicating them to stakeholders?

The spatial-related context offers an opportunity for richer presentation and visualisation methods for data, which could better support the sensemaking process and decision making for the team. In a multidisciplinary team setting, with varied expertise and perspectives of decision makers, how does an increased accessibility to and interaction with data change how people perceive the data as a tool for decision making? In what way does awareness of different characteristics of data affect the perception of validity and veracity, and the trust in data for use in discussions?

In settings such as the projects explored in this study, a team needs to achieve consensus with these multiple sources of data and perspectives. They need to be able to interact with the data, assess its quality and interrogate assertions, ultimately establishing trust in some of the data, reaching a shared sense of situational awareness, and making a decision. Some of the most granular decisions such as furnishings were made with the most autonomy as a group, with use of financial and construction program data of the project to understand the ramifications for decisions. The largest decisions that were made by the group involved the most interaction with related groups and an extended series of approval. These showed a much broader consideration for the strategy of the university, the motivation for the project, and the building in relation to its locality on the campus. For capital projects with institutional framing to the complex team decision making, there is more work that can be done to understand the relationship between the granularity of decision and the decision process. This would direct the sensemaking support requirements for these such as data treatment and presentation.

There will be challenges in transferring findings and observations from campuses up to cities. The differences in dimension and structure aren't trivial. Some campuses are small cities, and can act as testbeds, but their scale and operation benefit them in some ways that cities struggle. Campuses are mostly run by a sole owner of the buildings and infrastructure, and are favourable for implantation and acceptability of testing and technologies because of their student and faculty “citizens”. They draw private and public partnership well, and are manageable scales for groups such as the PMGs in this study to be aware of and account for concurrent and future projects. Cities are more distributed in their operating bodies, ownership and management of services and infrastructure, and the scale of population and consumption. This doesn't mean findings aren't transferable from campus, but there will be obstacles to translating technologies or practices beyond simply upscaling. There is complexity in the widening and diversifying of stakeholders and interests.

The exploratory study highlighted in long-term decision making some opportunities to better support group decision making with data. Reflecting on the findings back in the original context of smart cities, a wider variety of types of decisions could be considered. A model was suggested to provide structure to identifying where and how technical interventions could be developed to support decision makers. This model draws a relationship between the temporality of the data used by decision makers, and the time pressure of the decision they are making. A graph visualising this is shown in figure 3.1. This sketch is populated by a series of example group decision settings that cover different temporalities and time pressures.

The axes are non-linear but continuous, with labels but no axis ticks to highlight the loose or flexible definitions, the fuzziness that can be observed in these settings. The points or areas graphed are more relative than absolute. Here, high time pressure refers to decisions that need to be made over a matter of seconds to minutes. Medium time pressure captures decisions moving into the time frame of hours to days. Low time pressures cover those that take place over weeks, months, and years. Naturally, decisions can be made up of a series of sub-decisions, and this lends to the fuzziness that is in this model. Temporality of data has been split into four categories. Static data are mostly those without temporal nature, consider the built environment. The area between static and live could be described by a 5th label of temporary, for example data on roadworks in a city.

Some examples in figure 3.1 are explored in more detail below to demonstrate how this graphed space can be used and interpreted.

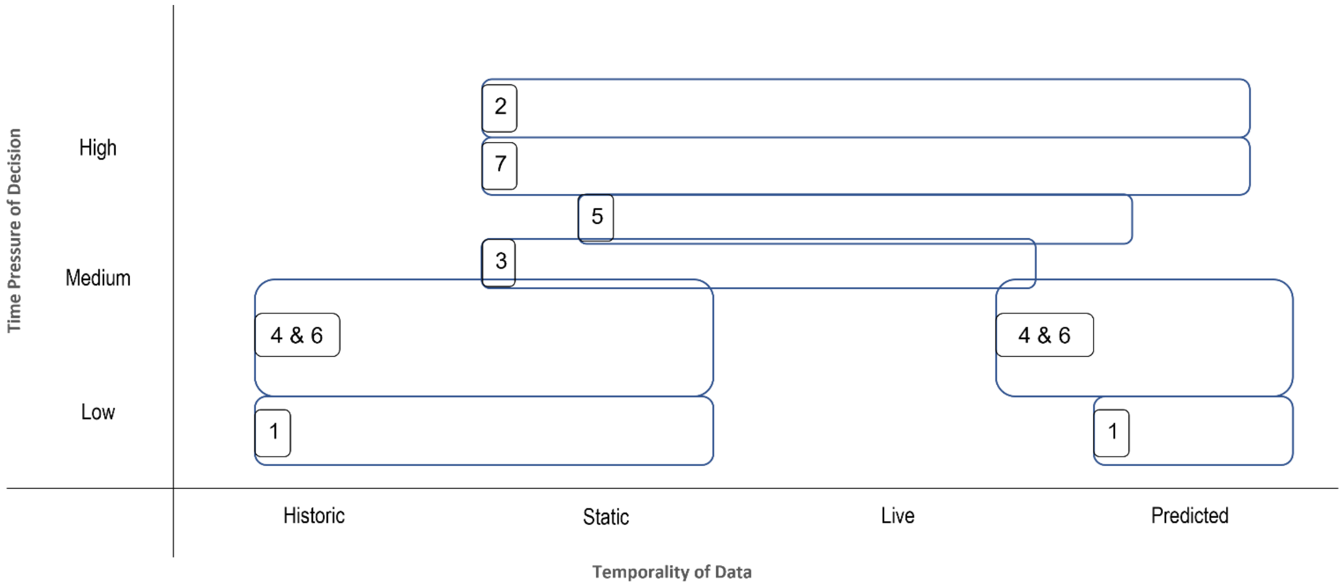


Figure 3.1 Graph of Temporality of Data and Decision Making Pressure

Example scenarios sketched on the graph:

1- Project Management Groups (University capital projects)
2- Emergency response
3- Event management
4- University Covid Response
5- Traffic Management
6- Local Public Health
7- Local Resilience Forum

The shapes associated with each scenario were sketched based on an understanding of the time scale of decision making for groups in the scenario, and the types of data used or available to them. The exact sizes and locations are relative rather than absolute. Positions have been used to indicate relatively higher or lower time scarcity for decision making in those groups, and presence of data of each temporality being used. The solid lines of the drawing don't convey the ambiguity or changeable nature of the scenarios, but as mentioned already the axis drawing and lack of ticks goes someway to indicating this. It is suggested that fuzzier lines should be used for more generalised settings, while lines could sharpen with increased specificity of a decision or scenario.

Each of these scenarios reflects a synchronous group decision making setting considered in this research for exploration for technical intervention opportunities through its lens of a smart city. Project management groups showed no use of live data in their decision process and made decisions over the longest period. Meanwhile, emergency response decisions were the fastest, most pressured, and with little apparent historic data use. Vertical size of the scenarios indicates the range of time pressure and decisions that happen in the setting. It’s common for all these settings to comprise a series of decisions or decision points rather than one singular group decision.

The shapes try to capture the range of time frames these decisions happen in. Horizontal distance has been used to try and indicate prevalence of temporalities of data in settings. Comparing 3 and 5, event and traffic management, demonstrates this. Traffic management in this case is being considered more responsive and based on live input of traffic and predictions of changes in traffic. On the other hand, event management is being considered more reliant on static and live data rather than predictive streams or models. They are both happening under roughly the same time pressure, with slightly shorter time scales for traffic response than event management. It may be more appropriate to draw less uniform shapes for settings. For example, emergency response, could be reshaped to widen around live data and narrow at either end, potentially asymmetrically, to reflect greater reliance on live feeds of information and the lower prevalence or use of static or predicted data.

The pattern of wider plots in the x direction rather than taller in the y direction gives more of a sense of a continuous decision scale. Gaps also indicate further settings to search for. A suggestion for the low-pressure-live-data gap could be an adaption of the traffic management of number 5 into control systems for traffic data or monitoring of training exercises.

This model and its use need further validation. For the purpose of this research, the graph provided a visual tool to explore the temporality and prevalence of data in different time-pressured group decision settings. The plots demonstrate contexts, environments, and activities of decision making groups. Characterising these settings can help framing opportunities for technical interventions and identifying potential transferability of findings.

Overlaps or distance on the graph could indicate ease or challenges of transferring results and applying interventions in new settings.

The timescales of a PhD meant focus for developing and testing an intervention would be medium to high time pressure decision settings. These settings would lend their speed of decision making to design and implementation of an intervention. Put another way, the low time pressure environments were too slow to fit in design, development, and testing within the remaining research period. Types of intervention based on the findings of this exploratory study would be led by those timescales.

4. Technical Intervention

The previous chapter laid out a number of directions for research based on an exploratory study of a group decision making scenario. In these findings was an indication that members of these groups trying to use data supplied to them hold a degree of uncertainty towards some of those datasets. For reasons of personal experience or areas of domain expertise, participants questioned the veracity of the data they were presented with but couldn't offer ways that they or the group had negotiated this. For example, the academics representing their faculty in the group were hesitant to accept and use the projected timetabled student numbers to guide decisions on room sizes. They felt that capacity requirements didn't need to be as high as timetables suggested because in their experience the in-person attendance rate of students is significantly lower than the projected numbers or size of the cohort that enrols. The range of perspectives presented issues with interpreting and assessing data they had been provided. Most indicated a desire to be able to interrogate the data they were uncertain about, to test assertions that were being made such as a requirement for space in a teaching room. These scenarios have time limitations, pressures on decisions to be made, and so supplying further data may not be helpful in all settings. The solution for specific groups may be introducing different data or more datasets that they are lacking. A more generalisable theme from the exploratory study suggested tackling trust in data and confidence in decisions in a different way. Rather than supply more data, the next step considers augmenting use of the existing data the groups have.

Data can be messy or unreliable. Metadata, and data quality information, could provide a way for the members of these groups to assess the data in their meetings, potentially reducing the feelings of uncertainty. To appreciate this and the significance in context requires training or experience in areas such as data science. Many members of these multidisciplinary decision making groups don't have this sort of experience. Though they may be domain experts for the area they represent in the group, they aren't necessarily equipped to interpret metadata, fitness of use, or reliability of data they are given. Similarly, there may not be sufficient time available in some of the decision making settings that were suggested at the end of the last chapter for group members to interpret and implement the additional data. Adding metadata, another layer of data, to a decision setting already rich in data, increases the volume of information for members to process. The additional load that needs sifting through and filtering can present a challenge in time pressured situations.

An abstraction or summary of metadata, an indicator of data quality, could present this additional layer of data in a way that doesn't overload decision makers. An appropriate abstraction needs to consider the concern already mentioned of adding more data, more text or numbers, to the decision setting and increasing the workload of decision makers. An abstraction that captures data quality in alphanumeric form may offer some benefit, providing data quality information to decision makers more succinctly than providing all the metadata, but still risks adding too much data for individuals to filter and assess. Alphanumeric abstractions, summary ratings of data quality based on the metadata, could also present a challenge of data presentation in an interface or documents provided to the decision making group. In a similar way, an abstraction could help multidisciplinary groups interpret data quality metadata.

Activity in other areas of research and design suggest a solution. Visual abstractions are already used to show ratings in systems such as nutrition labelling in the UK ('Check the Label', n.d.) and team management software ('Manage Your Team's Projects From Anywhere | Trello', n.d.). Food labels use a 'traffic light' system to indicate levels of nutrition categories in a packet of food, for example saturated fats in a sandwich with red indicate high levels, amber indicating medium, green indicating low. The criteria for these nutrition categories and thresholds for the nutrients are set out by the Food Standards Agency in the UK, and the system was proposed to help improve consumer decision making around healthier food purchases. This abstraction already exists, and though efficacy in this context is debated (Sacks, Rayner, and Swinburn, 2009), the format is likely to be familiar to many decision makers already. The concept isn't entirely new to decision making or to place-related data, with Devillers et al. (2007) already highlighted and Shankaranarayanan, Zhu, and Cai (2009) demonstrating ways a traffic light system could be used. The research for this PhD offers a way to do this and tests the intervention in an application and its effect on the data use and decision making.

It should be noted the difference in connotations of colour observed between Western and Eastern populations. Though in the West red is associated in standard design practice with negative values, this doesn't translate as strongly to the East (Yu, 2014; Chen and Zhang, 2021). This may limit transferability of findings for a traffic-light-based data quality abstraction in HCI and decision support design to Eastern cultures and populations, but the strength of effect is uncertain. Other colour combinations for a visually abstracted rating system could be explored if the same effects of the intervention aren't observed. In either case, colour blindness in the population also presents a challenge in this technical intervention. This is discussed as a potential limitation of findings in chapter 7.

The workflow for abstracting the metadata and updating the presentation of the data for the decision making group is represented in figure 4.1.

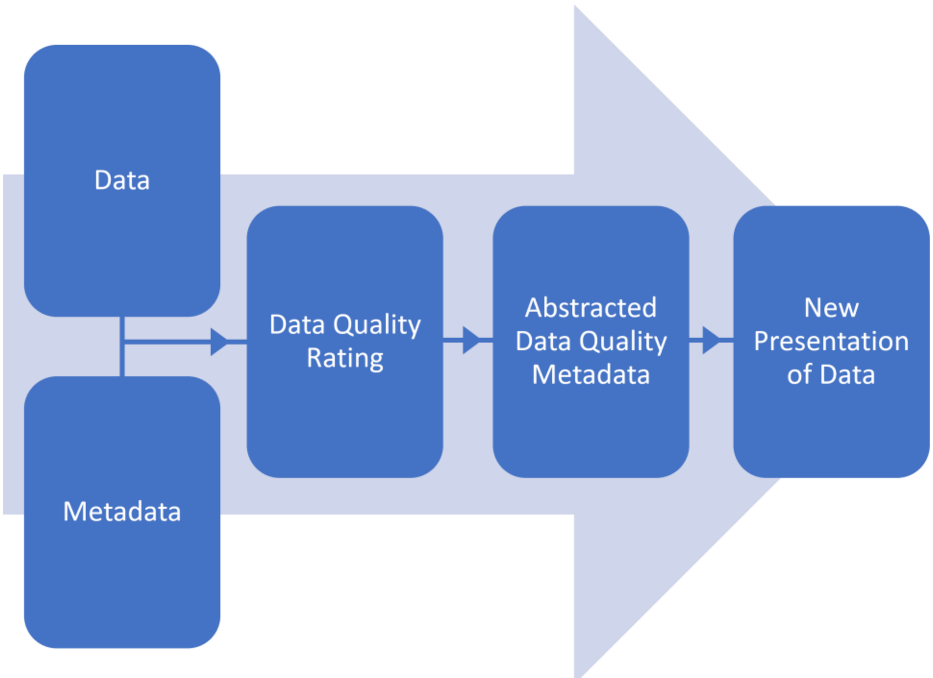


Figure 4.1 General Workflow of Abstracting Data Quality Metadata

This workflow is applied to a few examples from a fictional survey below to demonstrate the concept in practice.

Figure 4.2 shows an example of survey response data with an abstraction applied to the whole dataset. The data were assessed in context as high quality, with a high level of completeness (response rate) and recent data collection.

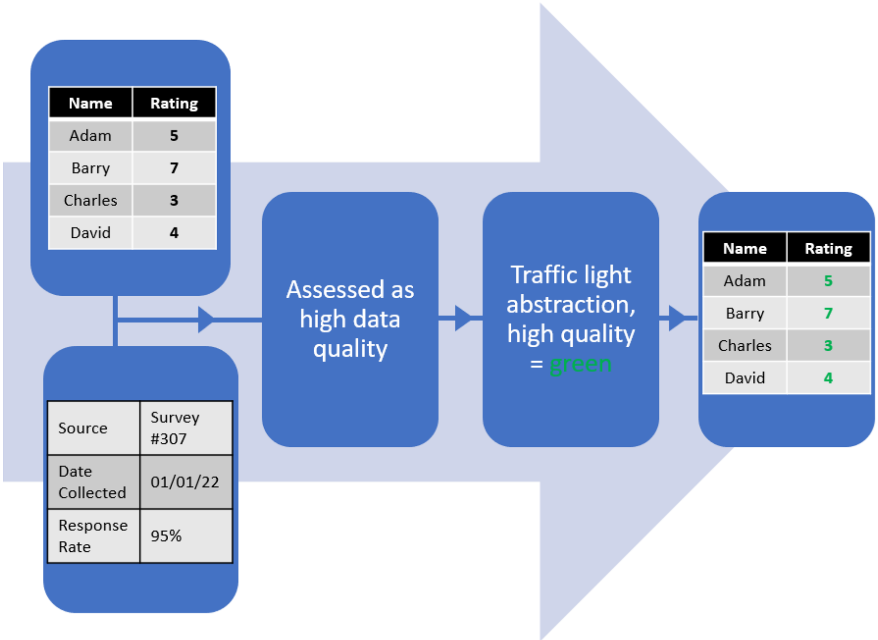


Figure 4.2 Workflow of Abstraction of Data Quality Metadata for High Quality Data Example

Figure 4.3 shows another example of this application with a lower quality dataset. Here the age of the dataset and lower completeness reduced the assessment of quality and its applicability to its context.

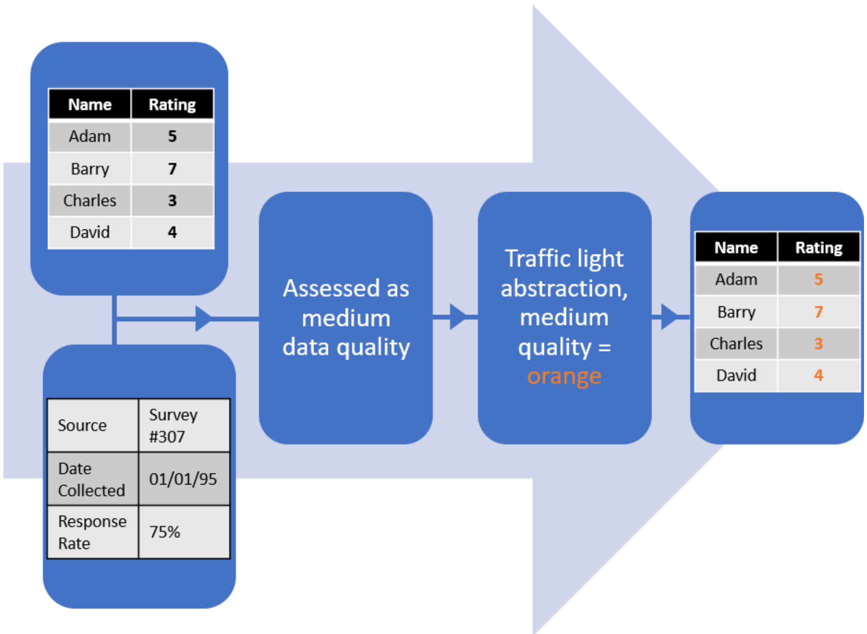


Figure 4.3 Workflow of Abstraction of Data Quality Metadata for Medium Quality Data Example

Figure 4.4 is an example of how the abstraction could be applied at a datapoint level to highlight variations of data quality within a dataset, for example anomalous or erroneous data. In this case, the dataset in general is considered good quality, but there is an erroneous entry that falls outside the scale of ratings collected in the survey.

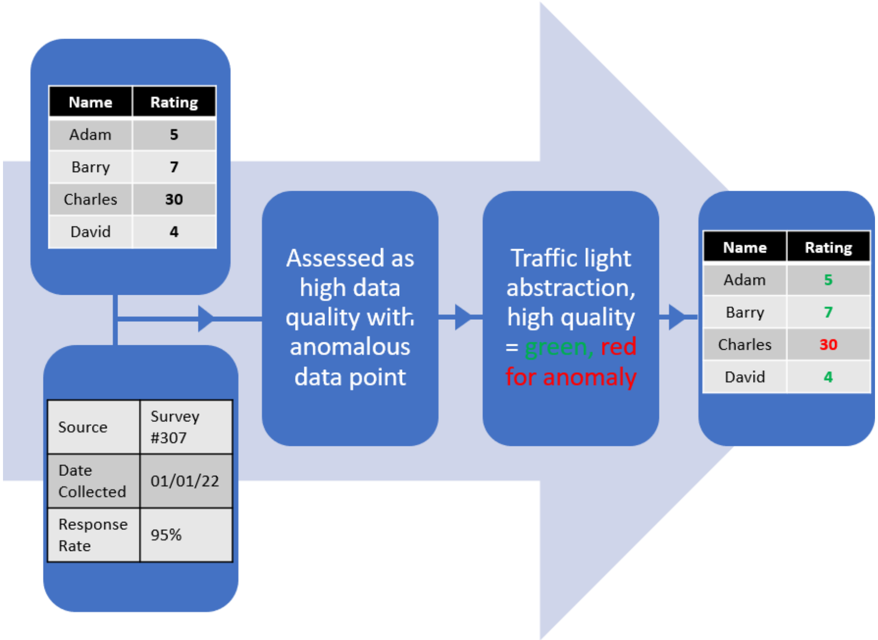


Figure 4.4 Workflow of Abstraction of Data Quality for High Quality Data Example with Anomaly

Metadata can come in different forms, it is data providing information about data, and so the availability and type for datasets is expected to vary. In the examples above there is provenance and completeness that could be used to interpret a quality rating of the data. This provides issues of generalisability or standardisation of methods of translating metadata into a data quality rating. Metadata are commonplace in databases, but nonstandard in the types stored or available to decision makers. For this piece of research, a test setting is identified for a technical intervention to be developed and tested, the issue of the range of metadata types and variety of decision making settings is discussed in chapter 7.

Using the time-pressure-data-temporality model presented at the end of the previous chapter, an opportunity is identified to design, implement, and test a technical intervention using this abstraction method in a medium time pressured setting. It's anticipated that there would be greater barriers to adoption and use in high time pressure settings. In these, groups are expected to be more likely to defer in the short time period to established processes and hierarchy to negotiate uncertainty in data. This would present a challenge for assessing the technical intervention effectively. Longer time scale decision making, low-pressure environments such as project management groups, still present opportunities to explore but were not feasible in the time remaining to conduct the research for this PhD. Settings that require decisions in the region of an hour present a better opportunity for an experimental study to implement and test an intervention. Settings towards either extreme of time pressure still offer valuable opportunities to study, this is considered as further work needed in chapter 7. The next chapter will describe the scenario being used to test an intervention, and the findings from implementing this data quality metadata abstraction in a decision support tool for group decision makers.

5. Design and Procedure of Experimental Decision Making Study

5.1 Introduction

This thesis has so far examined the low time pressure decision setting faced by project management groups, the extent of data use in these environments and the opportunities to improve them with an intervention. In order to conduct a study within practical timescales testing such an intervention, a medium time scarce setting was identified. This scenario maintains the place-related group decision making aspect of the research, now through the lens of a pandemic response team. This provided an opportunity to present a lot of data to participants with a time constraint that would promote groups needing to assess data quality and filter datasets.

Two versions of a decision support tool will present decision making groups with two levels of abstraction of data quality metadata. A control version is used as a baseline of data use by groups without access to any data quality metadata to understand the effects of the intervention. This study evaluates a technical intervention that offers users the ability to interrogate data and associated data quality metadata.

The scenario is a virus outbreak in a fictional region, and the groups are tasked to roleplay as the local pandemic response team to provide a proposal for the first month response to the outbreak. It is a constrained resource allocation task with a defined time for completion. The group members are working synchronously but locationally distributed.

The study sets out to answer research question 3 of the thesis – What is the effect of presenting data in team sensemaking as part of the decision making process?

To answer this question, the goals of the study are to understand the effects on the following aspects of the group decision making:

1. The interactions with the decision support tool.
2. The interactions between group members.
3. The decision processes.
4. The performance of the task (the decision time and outcomes).
5. The confidence of the group in the final decision.
6. The trust of the groups in the datasets used in the decision making.

Based on the related work explored in chapter 2 and findings of the study in chapter 3, the following hypotheses are offered:

1. Groups and participants that are provided metadata of either abstraction will have greater trust in the data used in the decision making than those without, and as a result, greater confidence in the decision made than those without.
2. The groups using detailed metadata will experience the greatest time pressure in their decision making and exhibit less methodical decision processes and interactions between members. The groups using abstracted metadata will experience the least time pressure.
3. The abstracted metadata groups will produce the best decision outcomes. the detailed metadata groups will feel as confident as the abstracted metadata groups in the decisions they make but produce the worst outcomes.

These effects are expected to happen because the introduction of metadata in either abstraction enables the participants to assess the data quality as part of their decision making process which can engender greater trust in the data, and subsequently confidence in the decisions made with that data. The detailed metadata groups will suffer from having greater volumes of data to process than either the control or abstracted groups in assessing the data quality. This will increase their experience of time pressure in the decision task and negatively impact the performance of the task, while they will still have confidence in the decision as a result of the trust engendering. Metadata could remove some of the uncertainty associated with data in these scenarios, but it adds another set of data to filter; the abstracted version should facilitate the reduction in uncertainty without significant increase in time to filter data.

This chapter is going to explain the methodology of this experimental study.

Sections 5.2.1-5.2.3 will describe the study location, equipment, participants, scenario, and the task that participants were given.

Section 5.2.4 will describe and explain the design of the decision support tool, the design of the data that sits behind and in the tool, and the metadata associated with that data.

Section 5.3 runs through the procedure of the study, how the three phases were conducted: pre-task, task, and post-task.

Section 5.4 outlines the data that were collected over those 3 phases.

Finally, section 5.5 outlines how that data would be treated and analysed.

5.2 Methodology

The ethics review procedure for the School of Computer Science at the University of Nottingham was followed and subsequently approved by the committee for this study (ID: CS-2021-R20). The primary concern for the researcher was the sensitivity of the study scenario topic, viruses and pandemic response, given the prevalence of Covid at the time. Efforts were made to fictionalise enough of the scenario to remove prior knowledge effects in the decision making, but also to remove the scenario from the real world setting to reduce potential distress. For the same reason, no details were given to participants in the study on the effects of the virus on people. It was determined that combined with these measures there was sufficient value in conducting the research, the timing of the study with the choice for the scenario and task would be engaging for participants while offering potentially useful findings.

This was an experimental study with qualitative focus groups. The below sections describe the scenario and task used in this study (section 5.2.3), the participants (section 5.2.2) and platforms (sections 5.2.1 and 5.2.4) the study was conducted with, the procedure followed (section 5.3), and the data collected during each stage (section 5.4 and 5.5).

5.2.1 Study location and equipment

As a synchronous distributed group decision making exercise, the study was conducted virtually on MS Teams between 26/04/22 and 10/05/22, with sessions lasting approximately 2 hours.

Participants were able to use the in-built Teams functions (voice, video, and text channels) along with the browser-based decision-support tool that will be described in more detail later in this chapter. Participants were also able to use other equipment or programs as part of the task to make notes, for example: pen and paper, a word processor, or a program such as Microsoft Excel. A copy of these would be requested at the end of the study.

The team exercise was recorded using the in-built Teams meeting recording function, capturing video, audio, and text channel use. The meeting recording function was also used to capture the post-exercise debrief and focus group discussion. The browser-based decision-support tool also captured logs of interaction.

5.2.2 Participants

36 participants were recruited across 9 groups of 4. The study used a convenience sampling method. Participants weren't domain experts; this was partly due to the difficulties accessing the number of participants from expert groups and controlling for expertise and familiarity with real datasets and models. Group members were familiar with each other, not strangers. Recruitment messaging asked for a single person to coordinate a team and to liaise with the researcher to sort times for participation. Groups with existing familiarity would mean teams had some existing group cohesion and reduced time needed at the start of the exercise to establish working relationships. All participants were aged between 18-35 years old. 8 of the 36 participants were females, the remaining 28 were male.

Groups were assigned to 1 of 3 versions of the decision support tool. In this way, each condition was assigned 3 groups of participants. Assignment was done in order of participation in the study, so groups 1, 4, 7 were given version 1 of the tool, and in the same manner 2, 5, and 8 to version 2 and 3, 6, 9 to version 3. The tool design will be described in a later section of this chapter. Participants within groups were assigned randomly to 1 of 4 team roles. These roles will be introduced and explained in the next subsection.

5.2.3 The Task

The Scenario

The scenario is a local region, a city and its nearby towns and villages, experiencing a virus outbreak and a 4-person team has been tasked with evaluating a list of candidate vaccination centre sites and recommending initial action to be taken. It is a constrained resource management and allocation task. The action is a proposal of the sites from the candidate list to bring into operation for the first month of the pandemic response to deliver vaccines to the local population. This is a moderate time pressured collaborative team exercise with individual role perspectives to reflect the multidisciplinary nature and varied interests within these groups, and synchronous group meetings bound to time limits to output a decision.

25 candidate sites are offered over 17 postcodes. These sites are mostly paired up or clustered so that groups may need to decide between sites in a postcode to avoid overlap or keep within constraints. The design of this map and sites will be covered in the next section but for reference a map of the local region and candidate sites is shown in figure 5.1 below.

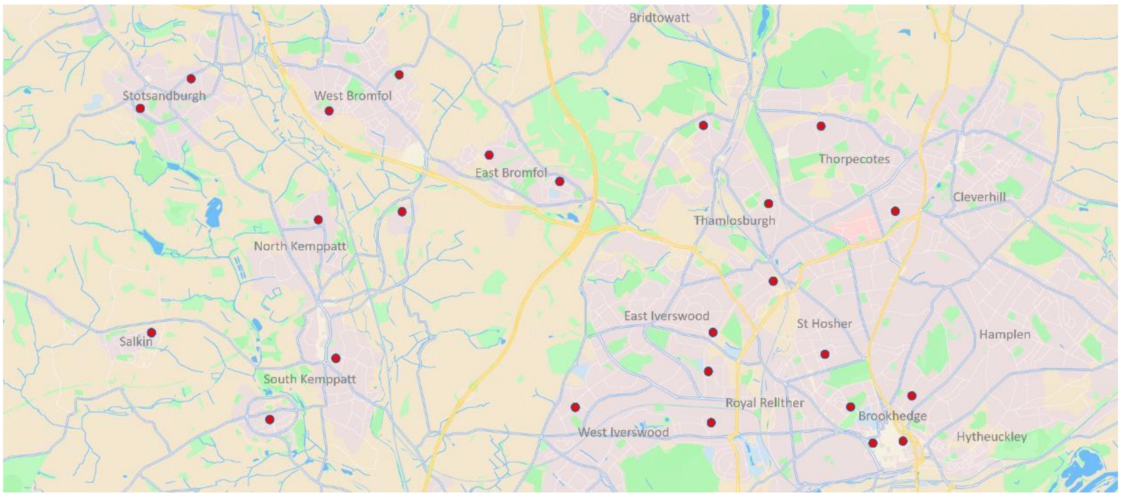


Figure 5.1 Reference Map of Region and Candidate Sites for Tool and Task Design

A main brief, included below, outlines the situation to the team and their main objective of the study task. The team, as a local pandemic response team, have been provided with a number of datasets associated with the candidate sites and the region.

Main brief to all participants:

“The area is suffering a virus outbreak, a local Pandemic Response Team has been assembled to put together an initial response for the region. The city of Portbridge, its boroughs and surrounding towns/villages, with a population of just under 300,000, need a plan for the first month.

This will be the first wave of vaccinations, so the budget and supplies are limited at this point. You’ll need to do the best you can with what we have access to now. 25 candidate vaccination centres have been identified in the region, your task is to select as many sites as you need and propose a plan for the first month response. You need to try and protect as much of the population as you can.

There are currently 2 vaccine options, PhasTech and BioMax, they have different supply levels and characteristics that you’ll need to take into account, the Logistics Official has information on this. By the end of the task, you’ll need to propose the list of sites that will be used along with some more details, and explain why you’ve chosen this plan.

Each of you has a different role with some additional information in your brief, you will also have access to this decision support tool with more information about the sites. You should take some time to read the rest of your briefs now before the task starts. You’ll have about 45 minutes before the Head of the Pandemic Response Team needs your proposal.”

The roles

The roles and role-related subtasks aimed to give each participant some more colour to their role, potentially increasing the likelihood that they adopt the role as a part of the team and engage more with the role-playing scenario. The subtasks were designed so that the individual goal wouldn't be too strong that it would overcome the main group goal and create any sort of adversarial behaviour, but to compete for some attentional focus during the task. They also softly guided members of teams to be responsible for evaluating certain dimensions of the constrained site selection problem, and gave additional motivation to the goal of the pandemic response team they were role-playing as. The 4 roles each lined up roughly to the 4 data tabs in the support tool, and each had additional data in their briefs related to these tabs and the role. This gives some ownership of different domains to different group members in the way you'd expect for similar teams and decisions in the real world. Finally, this distribution of subtasks and additional domain data would encourage participation from all team members in the scenario through a discernible benefit to collaboration, rather than 4 individuals working independently on the task.

The individual roles were a public health representative, transport representative, finance representative, and logistics representative. A summary of their briefs, subtasks, and additional data are below. Full versions of these briefs can be found in appendices D and E.

Head of Public Health

Subtasks: Prioritise vaccination of the most vulnerable groups. Minimise cases in the region in 4 weeks.

Additional data given in role brief: Information about the virus and its characteristics. Risk rates in age bands for infection, hospitalisation, and death. Current numbers recorded for cases, hospitalisations, and deaths. Statement on the effect of accessibility at sites on people travelling for vaccines. Some accessibility requirement statistics for the regional population.

Head of Regional Transport

Subtask: Minimise the reliance on public transport in the proposed strategy.

Additional data given in role brief: Information on the travel links in the region. Key road closures that impact opening and use of vaccination sites. Transport modality choice statistics for the region. Bus capacities and route information.

Head of Finance

Subtask: Keep the proposal within budget.

Additional data given in role brief: Outline that proposal budget is £4 million and that includes costs of site preparation and operation.

Head of Logistics

Subtasks: Minimise use of volunteers staffing vaccination centres. Minimise wasted vaccines.

Additional data given in role brief: Information on medically trained staff available in the region. Vaccine storage and handling requirements. Vaccine supplies for both manufacturers. Detail on impact of exceeding certain staff:volunteer ratios at sites on their opening timeline.

The three versions of the tool don't play into the task any differently in terms of instructions. For the sake of the task the abstract metadata version presents all the same data as the non-metadata version but with the traffic lights applied to the data sets. The detailed metadata version has additional metadata presented in the tool for each dataset (source, accuracy, and completeness). The visual differences between the versions are explored in the next section.

5.2.4 The Decision Support Tool

This section will explain what the tool does, the data that sits behind it, and the design choices that informed both the tool and data.

The tool is a browser-based map of the fictional region that presents data to the participants for candidate vaccination centre sites. It is a decision support tool in that it offers various datasets to aid the groups in making their proposal for sites to select for a vaccine roll out. It was designed as a web app to minimise barriers to participation in the study such as downloading software, being able to run a programme, and any administrative privilege issues. The tool was also designed in the browser to be usable on a laptop or smaller monitor, similarly, to minimise barriers to participation, maintaining a larger pool of potential study participants.

The tool was built using Bubble (‘Bubble Web-App Development.’, n.d.), a low code software development platform, a visual programming language based in JavaScript. Bubble handles deployment and hosting of the web app. These qualities enabled faster prototyping in the design stage and for faster deployment to conduct the study with participants within the timeframe available.

The purpose of the study wasn't about the design and building of a fully functional GIS-based decision support tool and database, but to create a valid and credible test case and platform for exploring the data and metadata use in group decision making. In this way, the tool resembles a bespoke GIS decision support tool, with features similar to ArcGIS and other existing tools for example, but with restrictions to enable the study to focus more clearly on the research questions. The background map was a static image with buttons, text, and icons overlayed to give the appearance of a fully interactable GIS tool.

The design process was iterative and included domain expert consultation and input, pre-empting decision workflows and interactions to guide the task and facilitate the purposes of the study. Also piloting features of the tool and study protocol with these domain experts ensured feasibility of the task within the timeframe offered to groups.

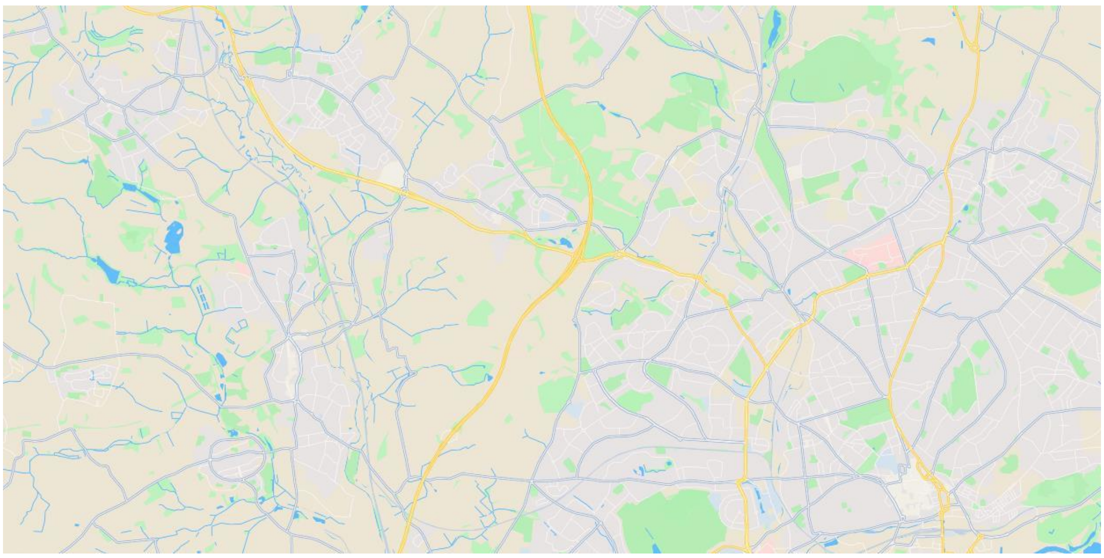


Figure 5.2 Base Map Of The Tool That Is A Map Of Nottingham And Local Area With Cartographic Labels Removed

Nottingham and some of its surrounding region was used as the setting for the study scenario, and so a base map with no cartographic labels ('Snazzy Maps - Free Styles for Google Maps', n.d.) was used as the basis for the tool. In the map in figure 5.2 Nottingham is in the bottom right of the image, the city was positioned in this way to remove the most identifiable landmarks of the map, such as the river, National Water Sports Centre, and university campus to reduce the likelihood of participants recognising the location and being influenced by any real-world knowledge. Prior knowledge wouldn't give participants an advantage in completing the task but could influence the decision making process for the fictionalised location and data. At the same time, basing the location on a real city and region provided the base map, and a pool of existing datasets to motivate and inform the fictional data. This will be explored more in this section.

The process of creating the fictional populated areas will be discussed later, but figure 5.3 is presented here to show the basis for the support tool. The underling map was split into rough population areas, 25 candidate sites were distributed across these areas. Sites were mostly paired or positioned close to other sites in their zone to try and force a number of decision points into the task for the participants.

Figure 5.3 Basis For Design Of Fictional Region Map Split Into Approximate Populated Areas And With Candidate Sites Plotted

Settlement and borough names were added to provide a framework to building the world and the datasets that would give the depth to the tool and scenario, shown infigure 5.4. The Eastern side of the map was left clear of sites to leave space for the planned tool interface design that would sit on top of the map image, but proximity to the city centre meant these populated areas were given names to include them in the service area for the task.

Figure 5.4 Fictional Region Base Map With Cartographic Labels Added For Settlements

The Tool

In this section a series of screenshots from the tool will highlight the interface, interactions available, and the data being presented to the participants. The base tool is the same across all groups in the study, with two distinct differences in the data presentation in the abstract metadata and detailed metadata versions. This section will highlight the majority of features using the non-metadata version of the tool, before explaining and providing the differences that would be seen by participants using the other two versions.

The interface on the web app is built on top of the base map, with different buttons comprising the UI elements that participants could interact with, and containers of data to toggle display to the right and below the map.

The following features that are highlighted and discussed are design choices made in anticipation of the user interactions and workflow in the context of the scenario, with some restrictions to control or limit groups for the purpose of the study and research questions.

In building a bespoke tool rather than developing the scenario within an existing GIS platform, there were some visualisation challenges in affordability of the interface. This is discussed further in the findings section for this study in chapter 6, but was an anticipated challenge given the planned recruitment of non-expert participants.

As will be reflected in the tool design shown in this section, for the purpose of the study and interface, the data was broken up into 4 main groupings, providing 4 data tabs for participants to access beyond any data in their briefs or displayed on the map. These groupings were emergent in the data design process, explored later in this section, and also from the domain expert discussions in the tool design stage.

Figure 5.5 shows the landing page for the study. At the end of the pre-task phase, detailed in section 5.3.1, the participants were each given their unique participant number, and then groups were given 1 of 3 4-digit study codes that would send them through to the appropriate version of the tool to start the task.

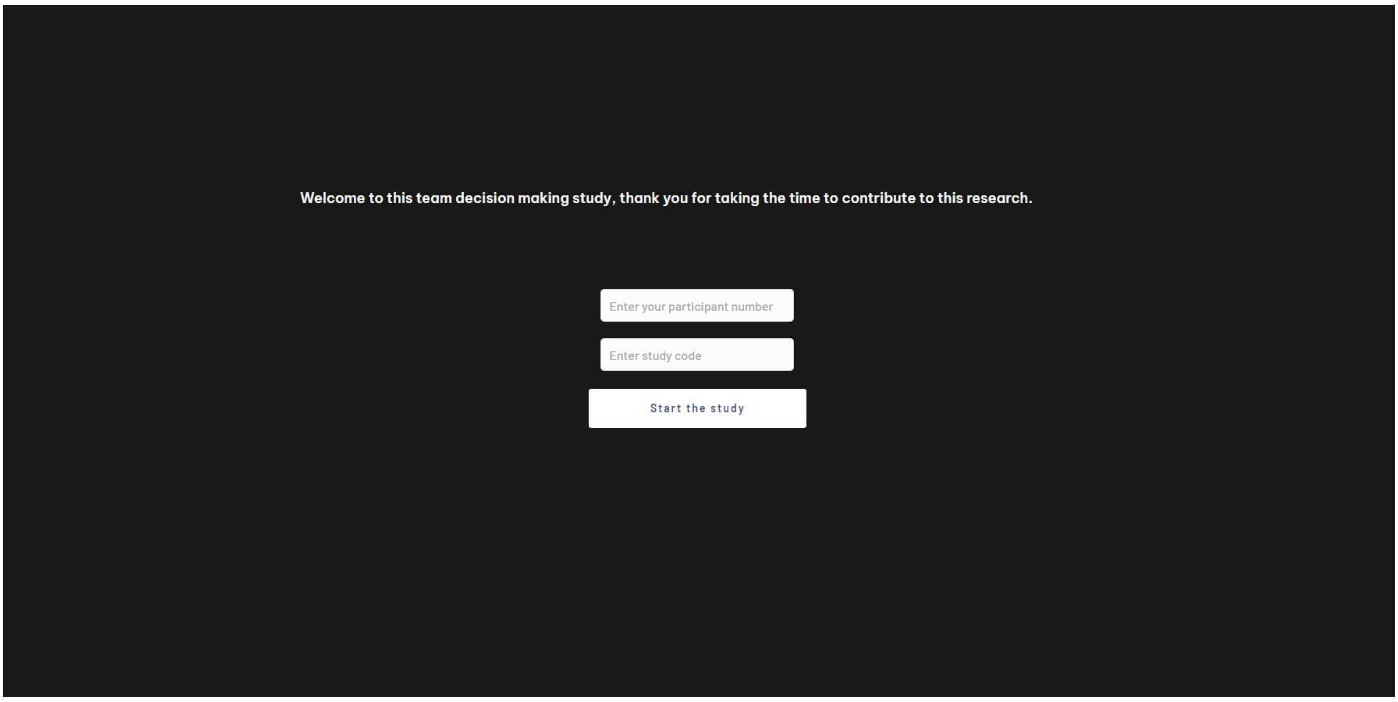


Figure 5.5 Decision Support Tool Landing Page For Participant Entry Of Study Details To Log In

After logging in, the participants are presented with the default view and selections in figure 5.6; no sites being selected, no datasets active, and the study brief in focus below the map for them to start the task with.

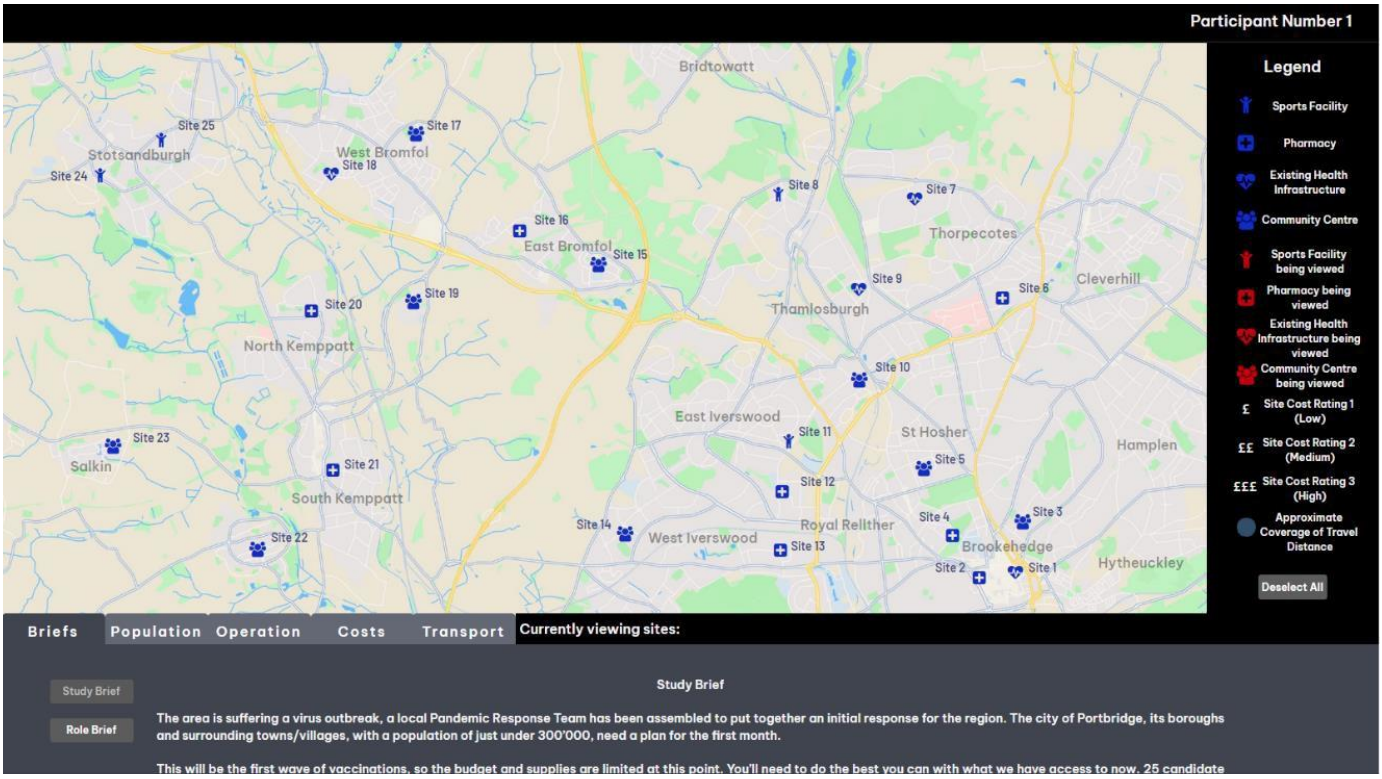


Figure 5.6 Initial Decision Support Tool Screen After Log In Showing Participants Base Map With No Sites Selected And Study Brief Visible

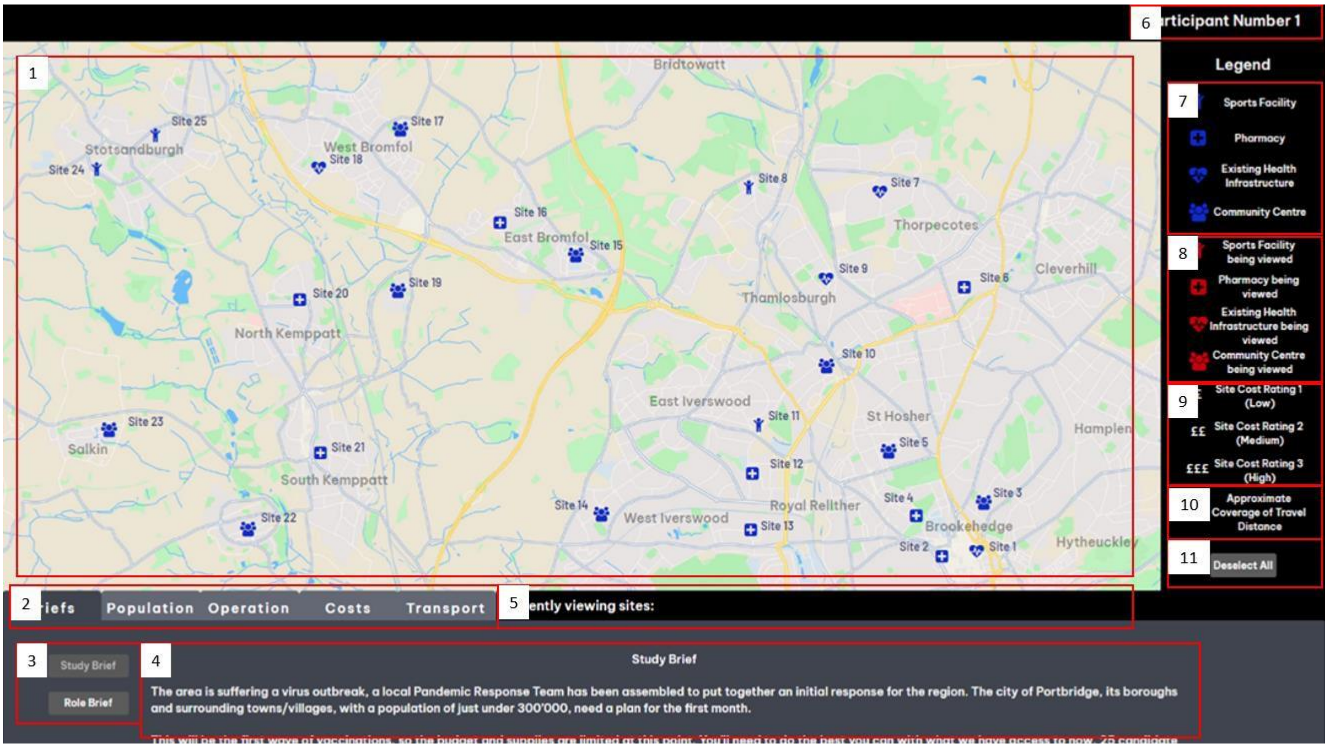


Figure 5.7 Default Decision Support Tool Screen Split Into Areas Of Focus And Interaction

Figure 5.7 breaks down the key areas and interactions on this view of the tool.

1- The base map overlayed with site numbers and icons. The 25 site icons are all buttons, clickable for the participant to select and deselect the site from their active list. Clicking a site toggles the state it is in and updates the active site list stored by the app, so clicking a blue site adds to the active list, clicking a red site will remove that site from the active list.

2- These 5 tabs control the data that is displayed below the map. Leftmost, the brief tab offers the study and role briefs to refer to. Then the 4 remaining are the previously mentioned data groupings that emerged in the design process. The active tab is highlighted, a tab must always be active. These tabs are also clickable buttons for the participant to select from.

3- When first logging in to the tool, the briefs tab is preselected for the participant, and in focus is the preselected main study brief. These two brief buttons can be toggled to alternate, with the text for the brief in focus darkened when toggled on.

4- This is the area below the map dedicated to the briefs and datasets. This page is scrollable, extending as the number of sites selected increases or between different length briefs. Figure 5.8 shows this in action.

5- The bar to the right of the tabs shows the participant the active list of sites that are being viewed on the map above, and the data for which will be shown in the section below the map. See figures 5.9 and 5.14 to see how this is displayed for single or multiple active sites being viewed.

6- The participant number in the top right confirms for the participant they used the correct log in credentials and is an interactable button that is used at the end of the task phase to submit the click log to the researcher before exiting the tool. See section 5.4 for further detail on this logging feature.

7- The top section of the legend aligns with the icons visible on first logging in for the participant, showing all sites blue and deselected, therefore not active, and illustrating the 4 different facility types available in the fictional region.

8- Below those icons the legend shows how each site icon will appear when a site is active and currently being viewed either by itself or as a multiple site selection. See figure 5.9 to see this.

9- These cost rating icons persist on the legend but only become visible when the costs tab is selected, figure 5.11 shows this in practice. This is a visual representation of some of the data in the study on the map to capitalise on the space available to use, and one of the ways the tool supports the group decision making.

10- In the same way as the features in box 8 and 9, this part of the legend persists but is only visible on the map when the population tab is selected. This is explained in more detail with figure 5.9 and 5.10.

11- Interactable button that enables the participant to deselect all active sites.

Figure 5.8 shows the web app scrolled down to reveal more of the brief below the map. The individual role brief for this participant is shown, with their instructions and additional data specific to their role displayed. Study and role briefs were put into the tab section below the map rather than appearing elsewhere such as pop ups over the map or being supplied in a document separately to the tool. This was to maintain a more continuous experience of the tool, keep the presentation of task-relevant information more uniform, and for the briefs to be more easily returned to throughout the task phase. Compared to the previous figure 5.7, the brief toggle button has switched highlight colour to reflect the role brief is in focus.

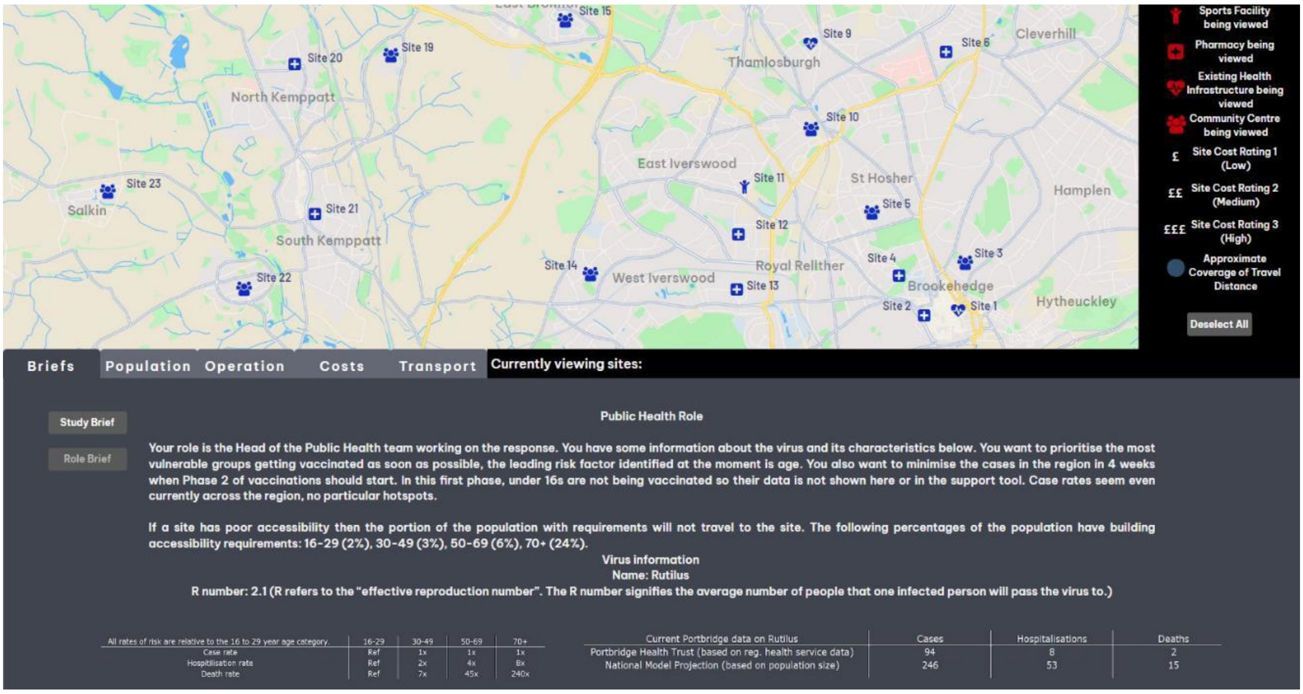


Figure 5.8 View Of Tool Below Map On Default Version With Role Brief In Focus

In figure 5.9 the selection of a participants first site is demonstrated. A single site is selected and active, now the ‘currently viewing’ bar updates showing the site number and the first line of its address. The icon for the site on the map updates its colour to show it’s active, and since the population tab has been selected the approximate coverage of the site using travel distance 1 is displayed. The travel distances and effect on population data will be explored in more detail in the next section. Here, it is sufficient to see that for active sites, when the population tab is selected, the participant is able to toggle between the two travel distance buttons 1 and 2. By default, travel distance 1 is preselected for participants logging in. With the first of the data tabs selected, the area below the map now updates from showing briefs to the relevant datasets for that tab, in this case an approximate breakdown of the population within age brackets that are covered by the selected travel distance (the population within the disc shown on the map). For the 4 data tabs, the first portion of the area below the map will always show a summary of data for all selected or active sites. Individual site breakdowns of data are displayed below this as shown later in this section.

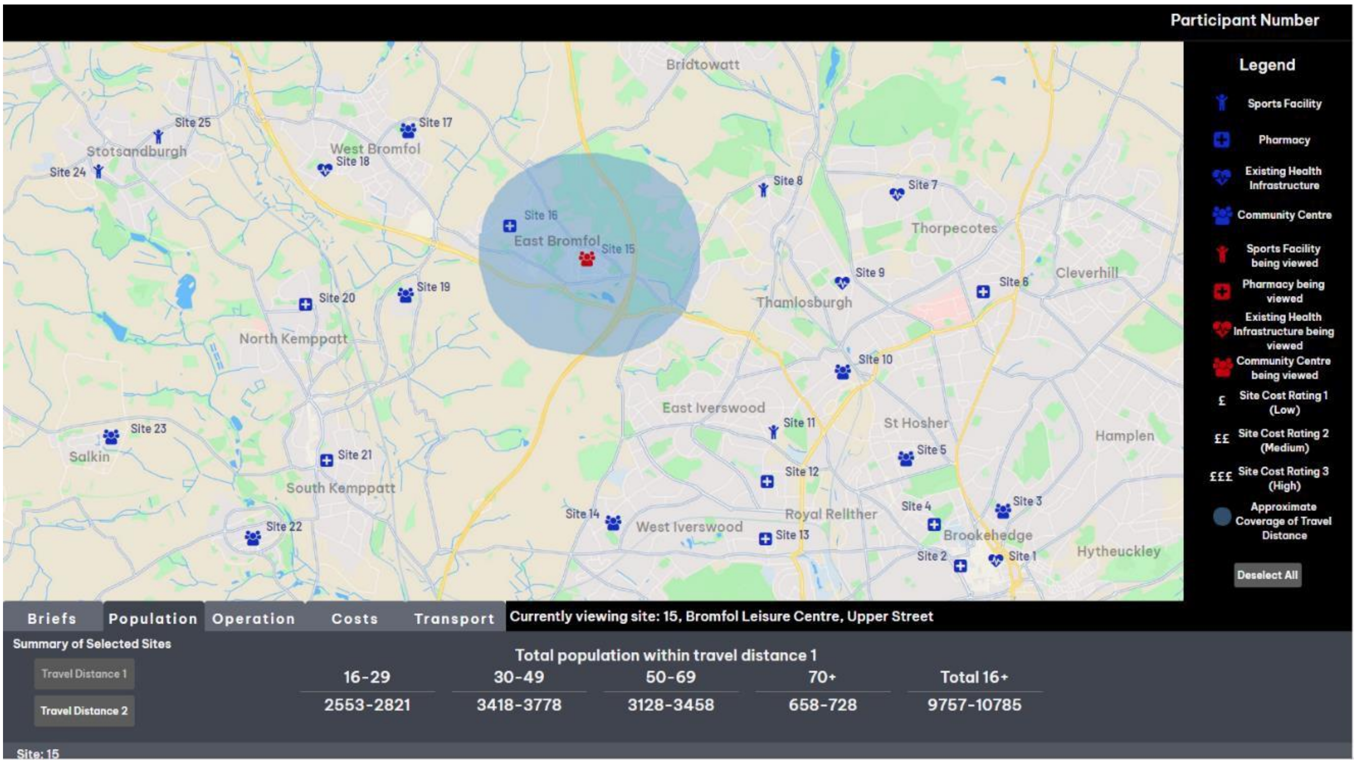


Figure 5.9 Decision Support Tool Demonstration Of Single Site Selection With Population Tab Open And Travel Distance 1 In Use

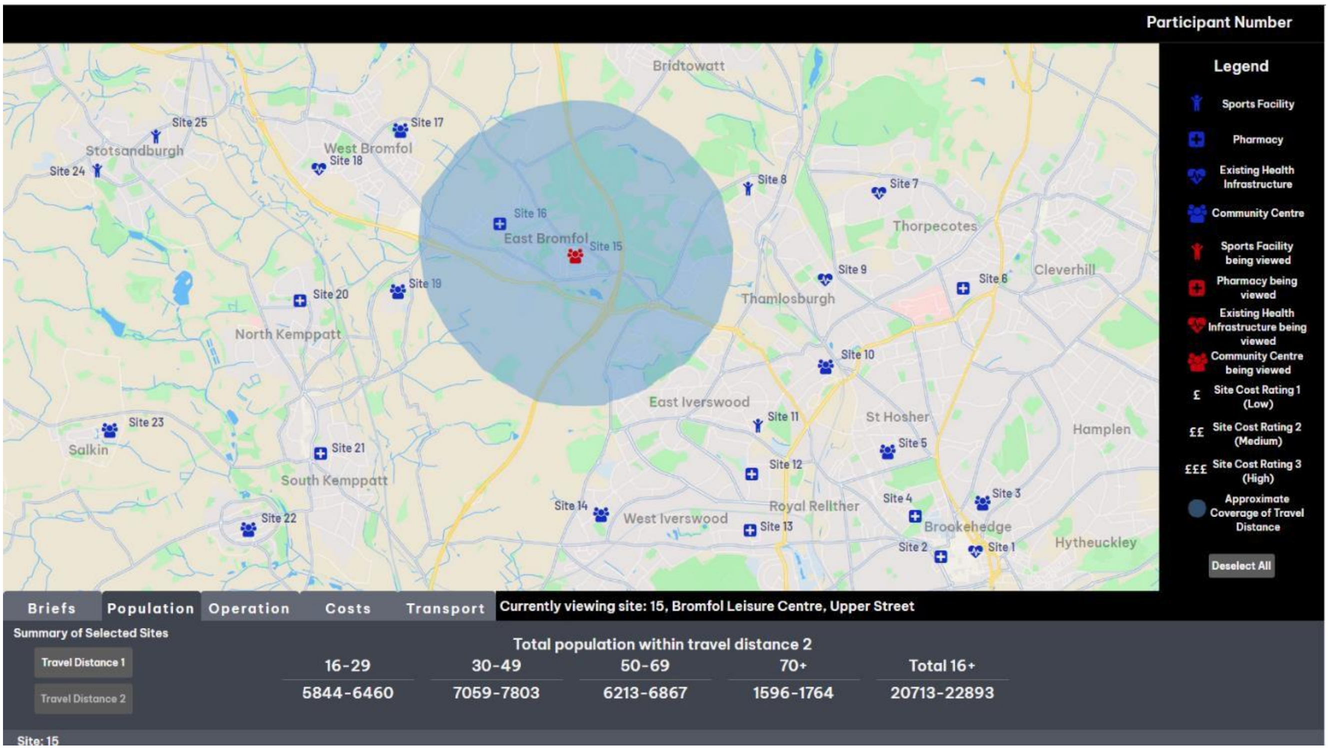


Figure 5.10 Decision Support Tool Demonstration Of Single Site Selection With Population Tab Open And Travel Distance 2 In Use

Figure 5.10 now shows the toggling by a participant from travel distance 1 to 2, the buttons and table header update to reflect this, along with the figures for the site shown below the map, and the area of the disc on the map around the active site 15. For each site there are two travel distance catchment areas that are shown on the map with discs in this way.

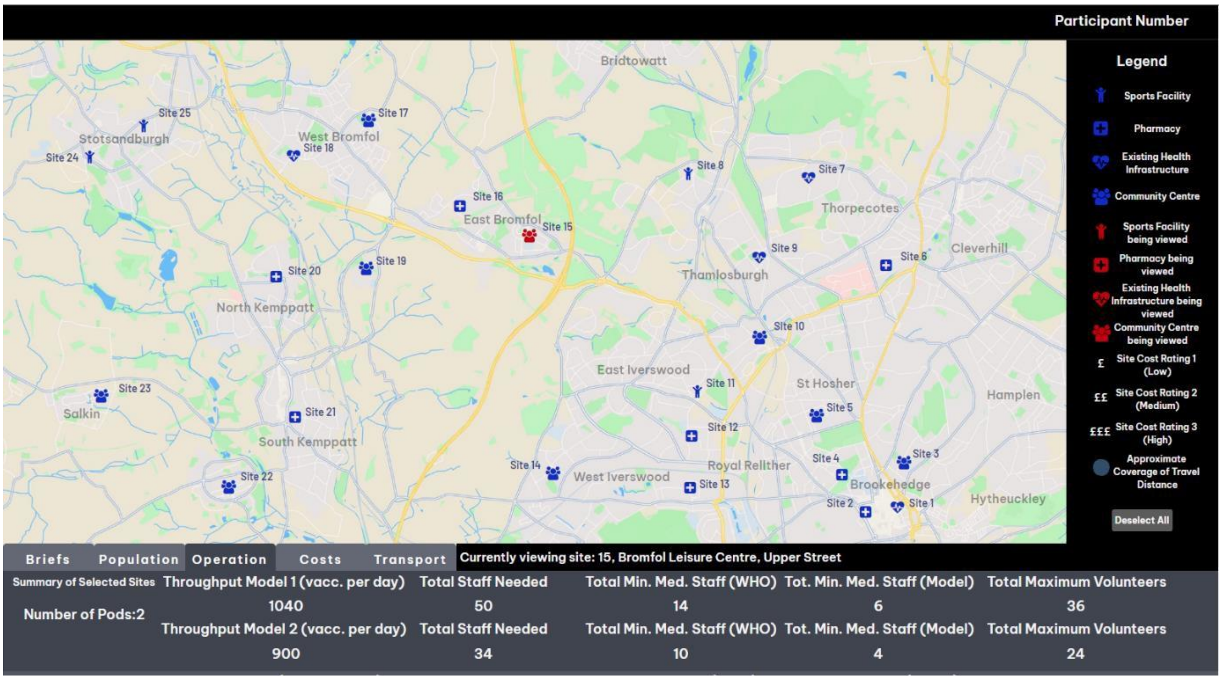


Figure 5.11 Decision Support Tool Demonstration Of Single Site Selection With Operation Tab Open

Across the 25 sites there are 3 different catchment areas for the travel distances, these reflect characteristics of the site location. Figure 5.15 shows this with two sites selected but two different travel catchment areas for the same selected travel distance. This is explained more in the next section.

These travel catchments don't persist on the map while participants move between data tabs, but the icon colour for active sites does. This was a decision to reduce potential visual clutter on the interface as participants navigated the data rich tool. The second data tab is shown selected in figure 5.11, and the table below the map updates with operation-relevant data. The datasets presented here will be described in the next section, but it can be noted for this data grouping there is no visual aid on the map, or interactable button.

With figure 5.12 the same can be seen as the operation tab as with the costs tab, there's no interactable button related to this data grouping, but in this case the map space is utilised to show cost ratings for each site. This extra dimension was intended, in the way the different site icons related to facility type, to assist the decision making process with visual representations of the more datasets shown below the map.

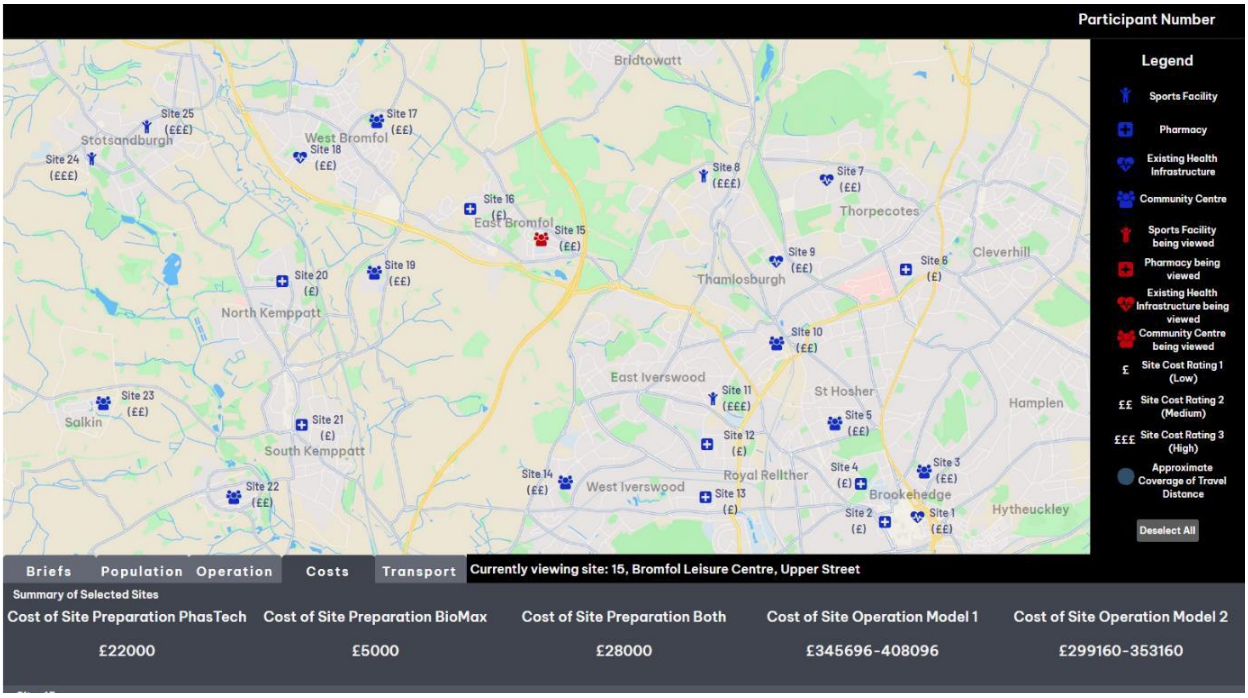


Figure 5.12 Decision Support Tool Demonstration Of Single Site Selection With Cost Tab Open

The final data tab for transport is selected in figure 5.13. There are fewer datasets in this grouping to show in the tables below the map but there is now a button available for participants to toggle showing and hiding bus routes on the map, also seen in figure 5.14. The summary data for the two right hand columns, bus stops and accessibility, refers to the dedicated rows for each site to see detail as these categoric datasets aren't aggregated in a summary. This was because, for example, there wasn't a sensible aggregation of accessibility ratings for active sites. This figure also shows an example of how individual site data are shown below the summary row below the map. In this case only site 15 is selected so only one site has a row below, but for each additional site selected the table extends below, and the participant is able to scroll down the page on the web app to see all the rows. The table updates each time sites are selected or deselected to present the rows below in ascending order of site number.

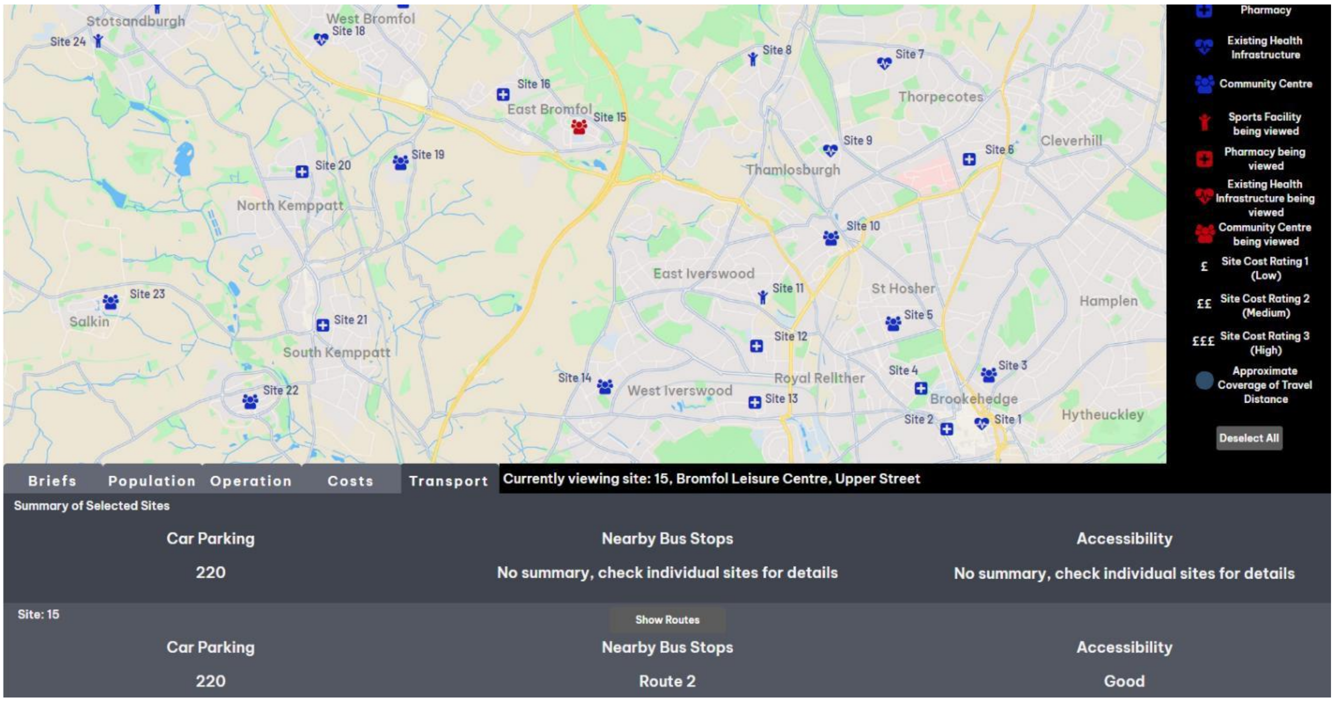


Figure 5.13 Support Tool Demonstration Of Single Site Selection With Travel Tab Open

Figure 5.14 shows the bus route overlay toggled on with the transport tab selected, and the bus route button has updated to show the action the participant can take, to hide the routes. Route numbers will be displayed if participants hover over a route. Information to identify routes based on the settlements they pass through is also retrievable from the Transport Official's role brief and by using the 'nearby stops' information for selected sites.

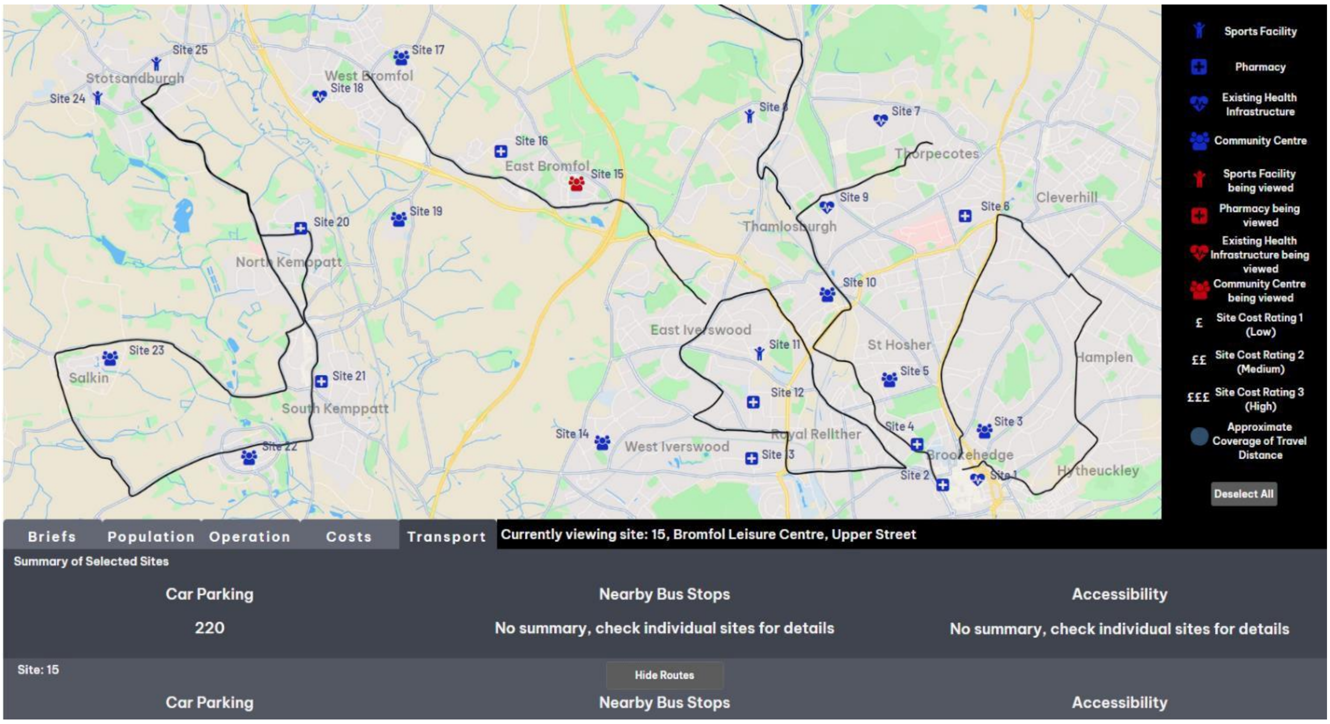


Figure 5.14 Decision Support Tool Demonstration Of Single Site Selection With Travel Tab Open And Bus Routes Shown

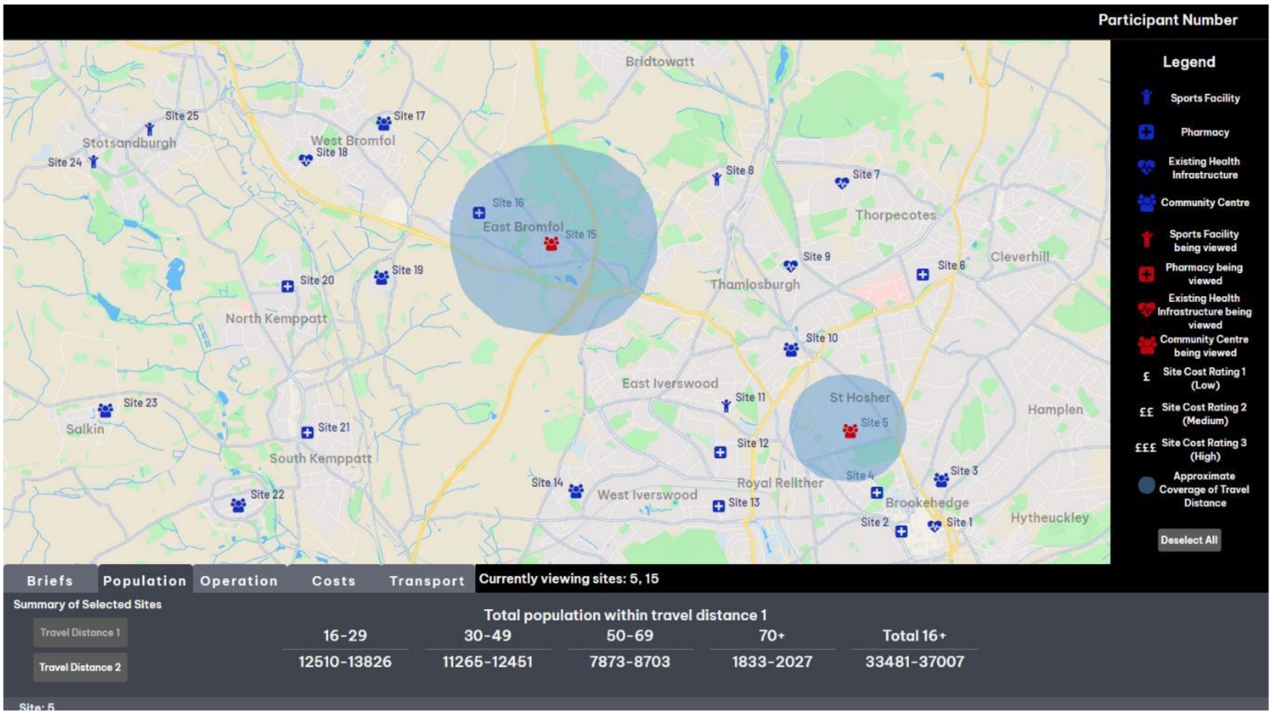


Figure 5.15 Decision Support Tool Demonstration Of Multisite Selection With Population Tab Open And Travel Distance 1 In Use

The next figure, 5.15, returns to the population tab selected to show the result of multiple sites being selected by the participant. Here two sites now update as red on the map to show they're active, and the currently viewing bar updates to list the site numbers for those currently selected. The address data are now dropped from that bar, visible only when a single site is selected, and there is sufficient room for the list to display all 25 sites numbers if every site is active. The summary table of population data still appears the same but is now updated with the aggregated data for sites 15 and site 5. The travel catchment area for the sites, using the selected travel distance 1, show how the catchment areas can vary depending on the location of the site in the region. These discs, though different sizes, represent the distance a citizen could travel under the conditions defined for travel distance 1, a function of transport modality and time. This variation of catchment areas across the region reflects real world transport speeds in different density areas and was brought into the interface to bring more meaningful spatial thinking and decision making to the task. As an example, site 5 in this figure is located close to the city centre, while site 15 is in a small town in the middle of the visible region.

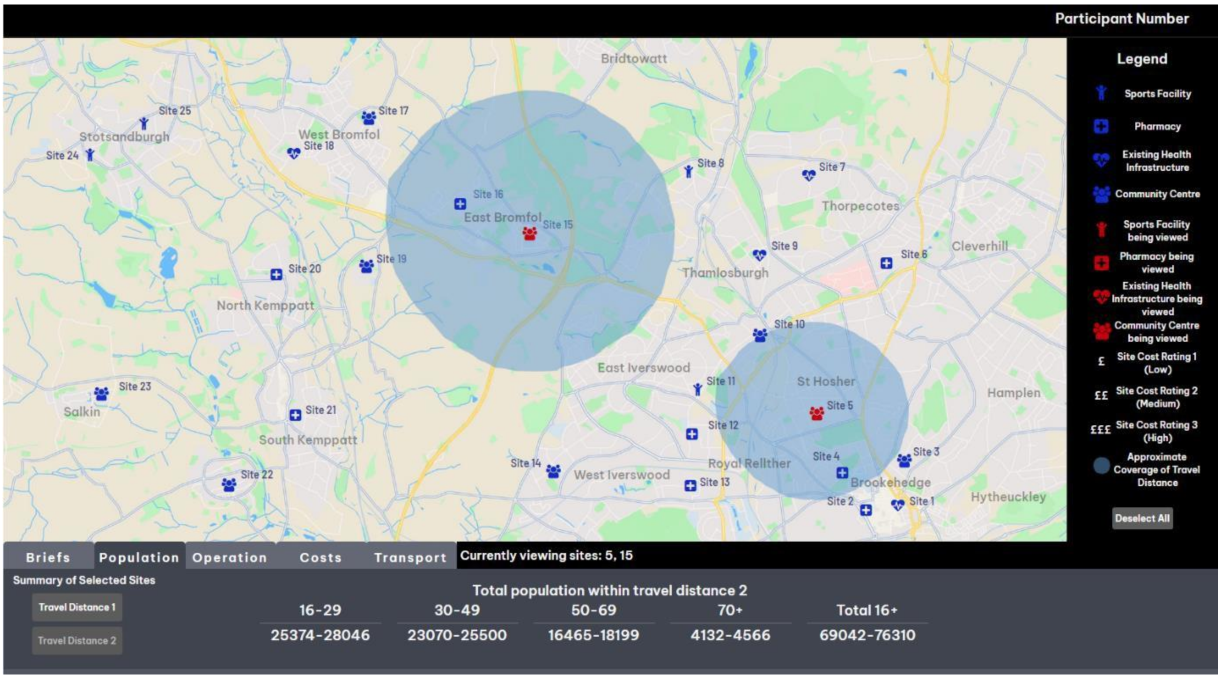


Figure 5.16 Decision Support Tool Demonstration Of Multisite Selection With Population Tab Open And Travel Distance 2 In Use

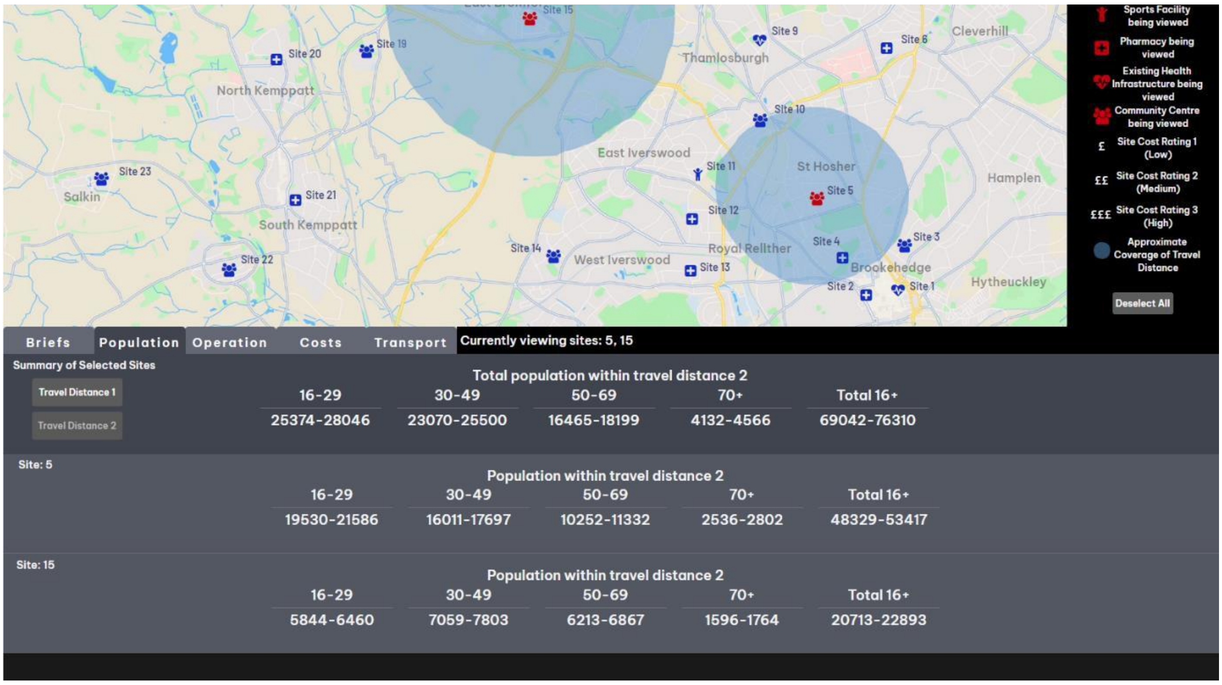


Figure 5.17 Decision Support Tool Demonstration Of Multisite Selection With Population Tab Open And Travel Distance 2 In Use That Focuses On Table Of Data Below The Map

The same relationship is shown in figure 5.16 as the travel distances in the population tab have been toggled, now showing the larger catchment of travel distance 2 which increases the time aspect of the travel function, giving greater population coverage for those sites but with relative characteristics maintained. Site 5 still has a smaller catchment area than 15.

Figure 5.17 demonstrates the multisite selection and presentation of data below the map. Each site, 5 and 15, have dedicated rows with their associated population data, and then these are combined for the top row summary data. This table extends down the scrollable page for as many sites that are selected and being currently viewed.

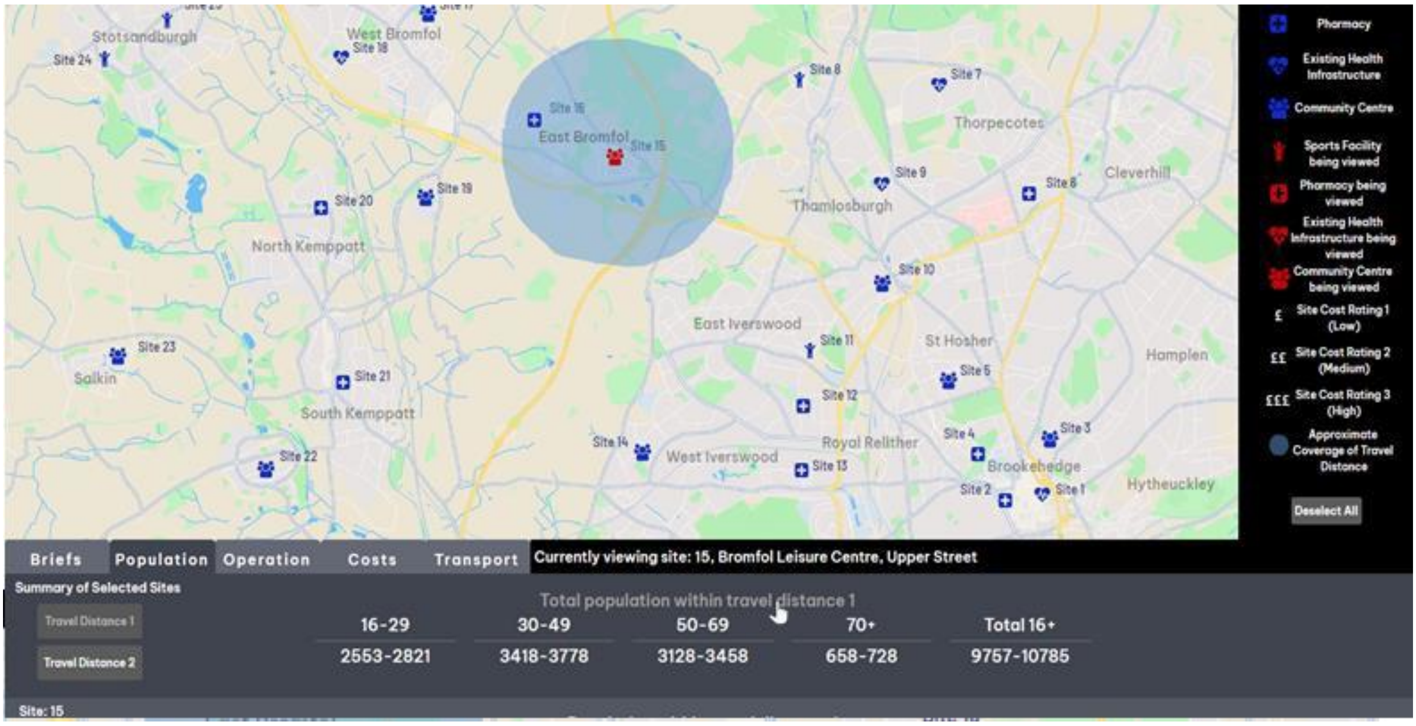


Figure 5.18 Demonstration In Decision Tool Of Hover Feedback Alerting Users To Interaction Option

The headers for the tables and table columns offer an interaction to the participants to find out more about each dataset, mostly to clarify or define the header where it may not be immediately apparent what that data represents. Figure 5.18 illustrates the affordability of the header interaction, with colour change of text on roll over, and also cursor change. To reinforce the presence of this extra information, participants were told about the feature in pre task steps. Clicking the header will toggle a pop up over the map relevant to that header and dataset. These headers also expand any abbreviations where they could cause issues for participants, such as in this same operations tab, total min. med. staff being the minimum medically trained staff needed at that site. These tooltips were needed to provide additional definitions or context that could be lost in short dataset headers in the interface, but also were the location for metadata in one of the versions of the tool explored below.

Figure 5.19 Examples Of Detailed Metadata Provision In Relevant Version Of Decision Support Tool

Figure 5.19 is from the detailed metadata version of the tool, and shows how the pop up tool tips were home to metadata as well as definitions and context. These two examples show the 3 data quality characteristics all datasets were given and shared with participants in the relevant study groups: a source for the data, completeness of the dataset, and accuracy of the dataset. The presence of this additional data quality metadata in the tool tips and briefs is the only difference between the standard version of the tool and the detailed metadata version. How these were chosen is explored in the next section.

These source, completeness, and accuracy figures weren't present in the header pop ups for the abstract metadata version of the tool, instead a traffic light abstraction of the data quality was used. In the top left of the interface shown in figure 5.20 the additional legend for this tool version is shown.

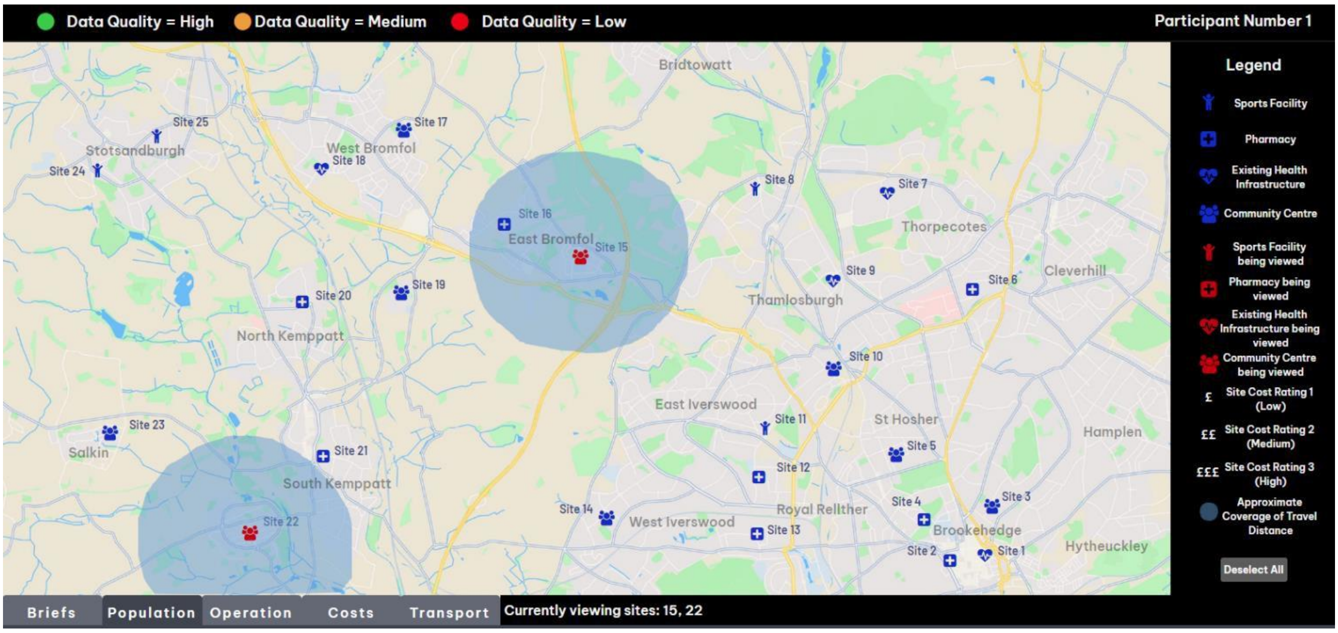


Figure 5.20 Abstracted Data Quality Metadata Interface Version Showing Traffic Light Legend In Top Corner Of Default View

Two examples of this traffic light abstraction being applied to the datasets in the tool are shown in figure 5.21. Each dataset in the briefs and tool had the data quality traffic light applied to them, here it's shown how some datasets had a blanket data quality rating given, such as population figures in the region. Meanwhile others had blanket ratings applied with exceptions for particularly datapoints, here the cost data was treated as high quality, but red figures highlighting datapoints that fell significantly outside the expected values. Literal red flags for anomalous data. The process behind assigning data quality ratings and colours to the data for the study is discussed later in this section.

	Population within travel distance 1				
	16-29	30-49	50-69	70+	Total 16+
Site: 13	862-952	1883-2081	2244-2480	974-1076	5962-6590
Site: 15	2553-2821	3418-3778	3128-3458	658-728	9757-10785
Site: 22	3766-4162	6871-7595	7059-7802	1291-1427	18987-20985

	Cost of Site Preparation PhasTech	Cost of Site Preparation BioMax	Cost of Site Preparation Both	Cost of Site Operation Model 1	Cost of Site Operation Model 2
Site: 13	£20000	£30	£240000	£172848-204048	£149580-176580
Site: 15	£22000	£5000	£28000	£345696-408096	£299160-353160
Site: 22	£220	£5000	£28000	£345696-408096	£299160-353160

Figure 5.21 Demonstration Of Visualisation Of Abstracted Data Quality Metadata In Tables Underneath Map For Population And Cost Tabs Of Selected Sites

The Data

This section catalogues the datasets that were presented in and sit behind the tool that the participants used during the task. It also explains how these were sourced or generated, and reference materials used to ground the constraints and problem in the real world to create a believable, engaging, and ecologically valid scenario.

The database that sat behind the tool was built in Microsoft Excel for export to the web app platform.

To identify appropriate datasets for the scenario, guidance was sort from papers and documentation that covered Covid responses, other vaccination programmes, and medical programmes such as reviews of dialysis service accessibility (McPhedran et al., 2022; Leithäuser et al., 2021; Petersen, Simons, and Patel, 2017; Mohammadi et al., 2021; Longhurst, Kremer, and Maysent, 2021; Farahani, SteadieSeifi, and Asgari, 2010; Weintraub et al., 2021; Risanger et al., 2021). These sources provided an initial list of the data that decision and policy makers used or recommended to inform rollouts of these population-wide access or distribution programmes. These included measures of; travel impedance, service availability, Jarman index (social deprivation), Townsend Index (material deprivation), Carstairs index (deprivation), DoE index (urban poverty), travel time, facility capacity, WIMD (deprivation), IMDm (deprivation), patient age, gender, ethnicity, income, employment status, location of residence, car ownership, travel cost, and travel speed. The potential list was then reduced to a manageable size for replication in the fictional region and down to a quantity that was considered practical for non-experts to grasp within the study time frame.

A particular challenge was designing the datasets and the associated metadata to have sufficient richness without overcomplicating the scenario and making analysis too difficult. It needed to be a believable multi-constraint problem, with realistic trade-offs such as medically trained staff and volunteers. One of these is a much more finite resource but necessary for operating vaccination sites, the other has a much larger pool, but bring a complexity with them of training requirements and supervision.

The basis of the research study also informed the choice and design of datasets for the scenario. The questions around uncertainty in data and negotiation of the truth directed some of the datasets and metadata that was associated with them. A framework the data design process was based on comes from Zimmerman’s summary of what and where uncertainty in data comes from (Zimmermann, 2000). The key sources highlighted for uncertainty were; conflicting pieces of data or the nature of data, measurement errors, abundance of information, linguistic ambiguity, subjectivity and opinions, and lack of information on the phenomenon or events.

An example of how this was incorporated in the scenario and data design was introducing two sources for one dataset, the staff needed for a vaccination centre, which introduces conflict for the groups navigating which number to use in their decision process. The metadata was designed to assist the groups in making this decision. Measurement errors could be seen in anomalous data points, falling well outside the ranges that the rest of the data points for that set appeared to be within. Therefore, participants would have a challenge of recognising these during the task, and subsequently how to handle them in their decision process. These could be flagged with the aid of metadata. Abundance of information is the primary aspect explored in the study, with a relative overload of information for all the groups in a time pressured scenario. The large number of candidate sites and datasets for each site meant the groups needed to find ways to navigate the task within the time given. Linguistic ambiguity is harder to define and build into datasets, given these were non-expert participants it was easier to use technical terminology or phrases to try and introduce ambiguity, as they may interpret headers or terms in different ways.

Not explicit in Zimmerman's list but available in this scenario and tool is spatial ambiguity that comes with place, place-related data, and the visualisation. For Portbridge, the fictional city and region, no clear outlines are given for the region, there is ambiguity or fuzziness in place names and how datasets such as population fit into these spaces. Subjectivity of opinions introduces uncertainty through how different individuals within the teams interpreted datasets or sources, rather than through design of the datasets directly. In the same way, lack of information on a particular phenomenon or event introduced uncertainty to the task with little need for design. There is limited information available about viruses in early stages of a pandemic, and even though the timing of this study means there is potentially heightened understanding of pandemics and viruses in the general public, there is a limit to the application of the Covid characteristics and responses to completing the task participants were given.

Virus characteristics

The virus name (Rutilus) was generated using an online name generator ('Virus Name Generator', n.d.). The characteristics, the rate of cases, hospitalisations, and deaths were based on accessible coronavirus risk figures available from the CDC in 2019, near the start of the global pandemic (CDC, 2020). The numbers of cases, hospitalisations, and deaths were taken from the UK figures from December of 2019, similarly near the start of the pandemic, and scaled to the population size of the fictional region ('Cases in the UK | Coronavirus in the UK', n.d.).

Vaccine information

The decision to offer two vaccines was intended to build a set level of additional complexity into the task, and introduce forced decision points (vaccine A, B, or both at each site picked) and another dimension to the vaccine constraint in the problem the groups were solving. The names were lifted from combinations of existing vaccinations, plausible but not real, BioMax and PhasTech ('Coronavirus (COVID-19) Vaccine', 2022).

Characteristics of these two vaccines were lifted from the data available on the Covid-19 vaccines approved in the UK at the time of building the study ('Coronavirus (COVID-19) Vaccine', 2022), though limited to simplify the decision points for this aspect of the task. One vaccine (PhasTech) was able to be used on all age groups being targeted in the scenario, 16+, and the other (BioMax) was only for 50+. The two were given different storage and handling requirements, this level of detail or expertise wasn't needed by the participants, but it provided the justification and motivation in the scenario for different facility preparation costs. Vaccination centres wanting to offer a vaccine that required specialist cold chain storage and resources would need to spend more to prepare the facility to do so, whereas offering a vaccine that only needed refrigeration would be cheaper.

Places – region, towns and boroughs, streets, and postcodes

An online name generator ('Town Generator', n.d.) was used to create the fictional region name and its constituent settlements or areas. The populated areas on the de-labelled map of Nottingham and its surroundings were divided into rough postcode areas, which were then used as the basis of characterised areas, to feed into the population data creation and the site types.

Each area had a postcode generated using the format prevalent in the UK, first 2 letters lifted from the post town PB for Portbridge, a number assigned that started at 1 for the city centre and worked in a roughly anticlockwise fashion moving away from the city centre, and the second half using a random generator to give an alphanumeric 2 -letter 1-number code for each site ('Random Alphanumeric Generator', n.d.). The site numbering system worked in a similarly systematic way. From there each site was assigned a random street name using another generator ('Street Name Generator | 1000s of Random Street Names', n.d.) to complete their address.

The site name and facility type were based on the types of facilities generally being used in the UK at the time for vaccination centres ('Coronavirus » Vaccination Sites', n.d.) and on the sorts of area in the real world that these places represented. This meant each facility was either existing health infrastructure (a medical centre/hospital), a pharmacy, a community centre (e.g. village hall or leisure centre), or a sports facility. These would bring their own characteristics later to inform other datasets such as costs of the facility, accessibility, and throughput based on size. Names for these were adaptions from the real list of UK vaccination centres referred to above.

The areas, divided by postcode, were characterised by the types of areas found in and around Nottingham, to inform the population data later. This meant each of the 17 postcodes were described as either a small village, large village, town, suburb, university area, high density residential, diverse mixed housing, retail/industrial area, and the city centre. These were given population descriptions, such as 'mostly small families and young professionals', or 'students', or 'families and retired population'. This characteristic informed a population skew for each area so that the region wasn't uniformly spread in terms of density or demographics, but also to reflect that most these areas in a city aren't entirely disparate either. Most postcodes were given two candidate vaccination sites to try and force groups over the course of the task into a series of sub decisions in making their proposal. The budget would not allow for all sites to be opened, so most postcodes could only support 1 site, or would need covering by neighbouring areas and their sites. This also reflected the density of vaccination sites operational in the early stages of the coronavirus pandemic in the UK, and general accessibility of vaccination sites and medical centres (Tao et al., 2020; Kiani et al., 2017; Silalahi et al., 2020; Hoseini et al., 2018).

Population figures

Generating population figures for the participants to use followed a structured 2-step process. The first step set the population for the region and its breakdown across settlements. The second allocated this to travel distance or catchment areas of candidate sites. By using a real map base, there were real population figures to base the population on before processing and skewing to fit the characteristics described in the paragraph above. For each populated area on the base map the real population figures for the corresponding settlement were lifted ('East Midlands (United Kingdom): Counties and Unitary Districts & Settlements - Population Statistics, Charts and Map', n.d.) and divided into age bands based on UK government archive figures from 2011 census (Nottinghamshire County Council, n.d.). The figures were then skewed based on characterised areas in the fictional region, before conducting the second step with travel distances from sites.

An example of how this worked in practice. Brookhedge in the fictional region, postcode area PB1 and home to candidate sites 1-4, maps onto a Nottinghamshire equivalent of the city centre, Radford, and Hockley, which have a combined real population of approximately 36,250. Using the age distributions and skewing to reflect the desired younger population in this area for the fictional region, the following were applied to that population number: 37% to 16-29 band, 27.7% to 30-49, 15% to 50-69, and 3.9% to 70+ band, total around 85% of 36,250. These produced numbers for each age band in postcode area PB1, which would feed into the population that would be covered by operation of sites nearby. The remainder were under 16 years old and for the sake of this study were being discarded due to complexity in government strategies at the time on vaccination of children. Figure 5.22 below shows part of this process of population generation for subregions.

Real pop		Adjusted pop distributions by age %				Adjusted pop distributions by age #				
		16-29	30-49	50-69	70+	16-29	30-49	50-69	70+	Total 16+
36238	skew young	37.9	27.7	15	3.9	13734	10038	5436	1413	30621

Figure 5.22 Excerpt Of Population Generation Table From Data Design Of Fictional Region Settlements

Travel distances and catchments

For the purpose of the study, a spatial-visual component to the decision making and support tool was important. The coverage of population by a site catchment area within a certain travel distance offered this opportunity and had grounding in the real world. The UK vaccination centres launched in the first wave of vaccinations during the coronavirus pandemic were distributed around cities. Taking those in Nottingham at the time of the first vaccination wave ('Coronavirus » Vaccination Sites', n.d.) a surface analysis put most residents in the city within range of 2-3 centres. This distance using the Google Maps navigation feature ('Google Maps', n.d.) put an individual in the densest areas within approximately a 20 minute walk, 10 minute cycle, or 10 minute drive to their nearest centre, and to the next 2-3 centres as alternatives around 35 minute walk, 25 minute cycle, or 20 minute drive. Numbers were rounded for convenience.

These times stayed fixed while distances changed as the location moved away from the densest urban areas to other parts of the region. This makes sense with the speed of navigating around city centres versus suburbs or between small villages. This provided two travel distances that were realistic and sensible for catchment areas centred around candidate sites. These provided easily visualisable components for the tool, and one of the main datasets that would sit in the table below the map. The approximate nature of these distances could introduce appropriate and sufficient uncertainty with them to the task, without needing significant work to create an accurate model of population given the time frame for building the study and the focus of the research. This varying travel distance and catchment area was refined into a travel distance 1 and 2 for each site. 1 being the smaller catchment and the standard, 2 being the extension a citizen might make to their journey to reach a second site.

There were three of these pairings, travel distances 1 and 2, splitting areas in the region into rough densities and assigning them to either high, medium or low. Sites in the highest density areas would have the smallest catchment areas for their travel distance 1 and 2, medium would have a slightly larger catchment, and low density areas would have the greatest catchment area by distance. As the next paragraph will show, this doesn't mean that low density areas would necessarily be able to carry out a greater number of vaccinations.

Step 2 to generate the population figures in the tool combines the previous two methods. Population density within a subregion of the map was assumed constant, but as above with the uncertainty in the dataset, this would be a strength of the data in the task for participants to navigate. For each candidate site, the appropriate circle for travel distance 1 as described above was overlayed on the map of the region. An estimate was made of the percentage coverage of each populated region by that circle. The population figure calculated was then scaled by that percentage for each region passed through by the circle, and these were summed to give a population figure for that travel distance catchment area for that site.

As before, an example to demonstrate how this worked. Site 3 is located in one of the densest parts of the region, so the smallest travel distance circle was overlayed on the map. The circle crossed through Brookhedge, Hytheuckley, and Hamplen, with estimated coverage of them of 45%, 15%, and 20% respectively. These percentages scaled the total population figures of Brookhedge, Hytheuckley, and Hamplen serviced by site 3 to a total of 18,046. Age bandings were calculated in the same way as described before.

This process was repeated for each site with their respective travel distance 2 catchment area. To reflect the uncertainty embedded in the steps to reach this population number for each site the data was presented as a range rather than single numbers, and for participants to have to handle in their decision process negotiating data and sites. Ranges were calculated using +/- 5% from the single figures that resulted from the above process.

Included in the brief for the transport official was an additional table of transport modalities related to these travel distances, and a statement on the increase in hesitancy to travel for a vaccination. This added an additional dimension to the decision making for the group using the population numbers, to account for potential drop off of people travel from certain age groups as distance from their home increased. This may encourage groups to develop a proposal that relied on greater numbers of sites to keep vaccination services more local to citizens in the scenario (Levesque, Harris, and Russell, 2013).

Site facilities

The site facilities and associated datasets, the costs, operation figures, and transport were built around a similar method as the population data. Real world sources provided guidance figures and methods used to model the set up at a site, the associated staff requirements, the throughputs of these centres, associated costs with running vaccination programmes, and considerations made when choosing sites. Considerations for potential real world vaccination hubs included; available parking, proximity to public transport, disability access, secure space for cold-chain facilities, connectivity to platforms on healthcare networks, and the size of space in relation to throughput numbers ('COVID-19: Vaccine Operating and Planning Guidelines', n.d.).

The decision to allocate each site to one of four facility types was led by the observed facility types in the Nottingham NG postcodes used by the UK government in 2021 ('Coronavirus » Vaccination Sites', n.d.) and the categorisation of sites by the Ministry of Health in New Zealand ('COVID-19: Vaccine Operating and Planning Guidelines', n.d.). For the UK, sites were either designated vaccination centres at former and current industrial estates, pharmacies, GP-led services, and hospital hubs. GP-led sites included village halls, leisure centres, university campus buildings, and recreation grounds. In New Zealand, sites were identified as either Family, Community, Large Community, or Large Metro. Examples of what sort of facilities these categories covered are in figure 5.23. Combined, these established the 4 categories that would be used in the fictional scenario and direct the datasets. These were Pharmacy, Existing Healthcare Infrastructure, Community Centre, and Sports Facility.

Figure 5.23 Extract From Ministry Of Health New Zealand Covid Documentation Showing Categorisation Of Vaccination Centres

The published NHS models were used as a framework for characterising the site sizes and operation figures, with detail stripped away for the groups to reduce some complexity in that aspect (‘Workforce and Training: COVID-19 Vaccination Programme - Reviewing Workforce Requirements for Vaccination Centres’, n.d.). Figure 5.24 shows an example of the NHS recommendations for workforce and site layouts for one of the vaccines under one of their models. This lists all the roles required to run a site and demonstrates the modular pod system that vaccination sites can use, and the volume of vaccinations per day. This would carry into the fictional sites with the exact roles removed and just summary staff numbers needed to operate a pod. This source also directed the offering of two pod models to groups, with a second model for each site that would reduce the staff needed, to reduce pressure on healthcare practitioners, but with a starker difference in the staffing levels and effects on throughput than was listed in NHS guidance.

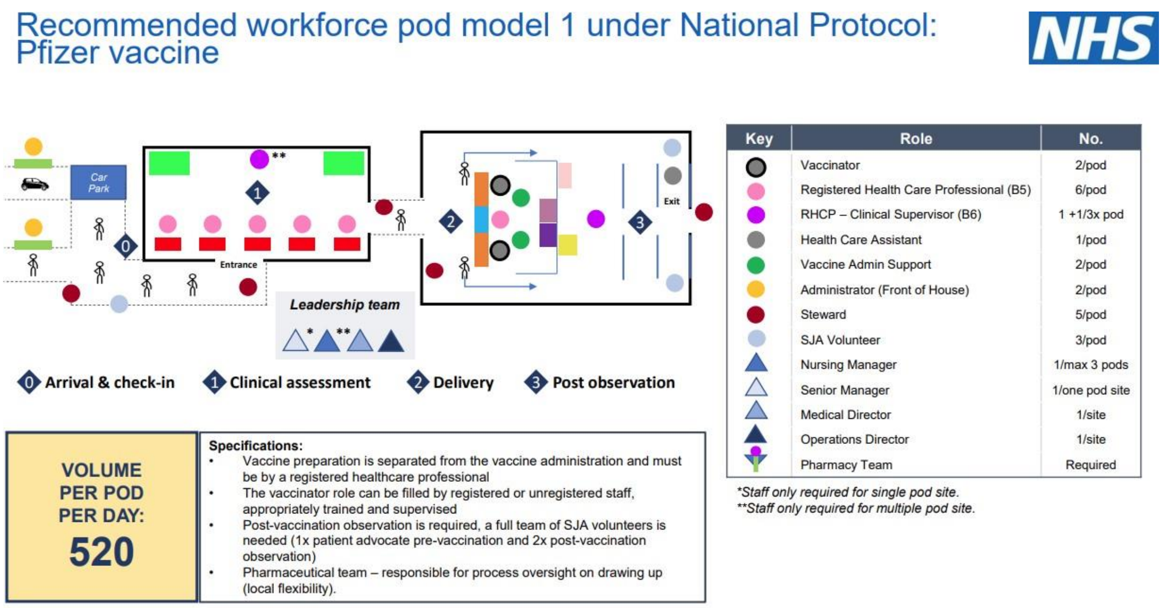


Figure 5.24 Extract From NHS Covid Documentation Showing Recommendations For Staffing Of Vaccination Centre Pods

The model pod maximum vaccinations per day is generated by different distributions of staff between vaccinator and other roles, the rate of vaccinations by one vaccinator, and an expected time for an individual patient to pass through the whole pod from arrival to departure from the site. Model 1 in the study uses the standard volume suggested by the NHS, a pod max per day figure of 520 vaccinations, while model 2 gives a reduction based on a 70% staffing level, leading to a pod max per day figure of 450. 25 staff would be needed for the model 1 pods, and 17 for the model 2 pods at any site. Using the NHS protocols for vaccine delivery, each pod was assigned a minimum number of medically trained staff required, and a maximum number of volunteers that could be used to operate the pod.

Two figures for the medically trained staff were offered to introduce a decision point for groups, to navigate which source or figures to use in their decisions, and to reflect the uncertainty in materials in the early stages of the coronavirus pandemic. The pod models were described as “agnostic to vaccination type” at the time of approval and so maximise vaccination throughput of a pod within some safety limitations, without regard for differing vaccine requirements such as supervision during wait periods and cold-chain management (‘Workforce and Training: COVID-19 Vaccination Programme - Reviewing Workforce Requirements for Vaccination Centres’, n.d.). These figures, the throughput for either model, the staffing requirements and constraints, were all functions of the pod number. Therefore, these datasets for each site could be calculated by multiplying by the number of pods for that facility type.

The four facility types listed earlier, pharmacy, existing healthcare infrastructure, community centre, and sports facilities, were given a size, and an associated pod number. Pharmacies would be the smallest sites and host just 1 pod. Existing infrastructure such as portions of a local hospital and the community centres would both contain 2 pods, this shared size would introduce some decision points to the task where sites of the same size in close proximity would need other datasets to be used other than throughput to select one. The sports facilities would be large arenas and stadiums, with the space and transport infrastructure to support 4 pods.

Site costs

Divided into these facility types with assigned pods numbers, staffing levels, and throughput figures, the sites could have operation costs attributed to them. Costs of these sites split into upfront site preparation costs and then general running costs. Preparation expenses ensure sites have appropriate storage facilities, equipment, staff training, and signage to deliver vaccines. Operation costs are influenced by building rent, staff costs, utilities, additional clinical supplies, and the costs of the vaccine.

The NHS uses an Item of Service (IoS) fee ('NHS England Items and Fees Dispensed | NHSBSA', n.d.), which for vaccines reduces this exercise down to a single figure that represents the cost to deliver a single vaccine to one person. Combining what is covered so far, a facility type dictates the number of pods being used, which dictates the vaccine throughput of the site, which gives an estimate of the cost to run that site delivering that number of vaccines. Though the NHS give a single IoS fee, in this study a range was created around a single fee to introduce some more explicit uncertainty to this dataset for participants, and to reflect how these costs so early in a vaccination programme have inherent uncertainties. The £12.58 IoS fee for a Coronavirus vaccine at the time of the study (Dyson, n.d.) was used, and just +/- 50p to create a range on a single vaccine. An estimated operation cost for a month was calculated from this IoS fee range scaled by the maximum vaccine throughput for that site using the standard model 1 or reduced staffing model 2.

Preparation costs are independent of the IoS fee and are a function of the facility type assigned to each site and the vaccine or vaccines planned to deliver there. Existing healthcare infrastructure already have the cold-chain facilities needed for BioMax and PhasTech. The other facilities would need specialist equipment such as ultra-cold freezers that cost in the region of £20,000, along with clinical equipment and staff training to prepare them to deliver the vaccines (Banerjee, 2020). Each facility type was given a preparedness-for-vaccine-delivery rating and a cost to reflect this for the two different vaccine types and the option for delivering both at a site. The order of expense for a site to be suitable to host a vaccination centre was, existing health infrastructure, pharmacies, community centres, and then sports facilities. This was a combination of their preparedness rating and size. The combination of these preparation and operation costs showed emergent bands of facility type and a cost rating, low, medium, and high, as seen in figure 5.12 in the previous section on the use of map space to display data.

Transport

The final datasets connected to sites fall under transport. These were all generated on a site-by-site basis rather than applying general numbers to each facility type. Part of the consideration for vaccination centres as highlighted before is car parking. For this scenario, the car parking figure was generated combing the facility size with the urban density of the site location. This meant that large facilities such as sports venues located on the outskirts of the city would have a large number of car parking spaces, while a pharmacy near the city centre would have only a few.

The public transports connections were designed visually. Using the region map and settlements, 6 realistic bus routes were sketched and approximate carrying capacities of the route were attributed to them. Denser urban areas were given more transport links. Bus stops weren't chosen, instead nearby bus stops were attributed to a site if a route passed close by. This phrasing, "nearby bus stops", was left purposefully ambiguous in the bus routes presented to participants to introduce another source of uncertainty through ambiguity. Individuals may have different interpretations of what is defined as near if they aren't explicitly told.

Site accessibility was rated in a similar way, sites were assigned either "good" or "poor" and the task left to participants to negotiate the significance of that rating and how to interpret its effects on delivery of vaccines to different populations at that site. Just 4 sites were assigned the "poor" rating, site 2, 12,16, and 19. These were chosen as they were in tight clusters of other candidate sites and were comparable on most other variables that could be considered for those sites. This added another defined decision point if the participants weighted the accessibility rating with any significance in their decision process.

These last three datasets, parking, public transport connections, and site accessibility, were designed mostly as superfluous datasets. They contributed to the world building aspect of the scenario and could help enrich the task for participants and their engagement. They are also factors included in real world considerations, but they weren't designed as main factors for groups to select or discard sites. Instead, they offer a few datasets that add to the volume of information participants are presented with and need to filter and process while negotiating the task; they're distractions from the key datasets such as population coverage, operational costs, and throughput figures.

Road closures were added in two places in the region as a form of temporary or live data. This wasn't presented in the Transport Official brief as a clear list of sites affected, but in a sentence on the two roads closed and the town/borough they were in. The participants would have sufficient information to identify the two effected sites and to dismiss them from consideration, but this would be a challenge for each group in the context of the bigger task and set of information.

Each role had some data presented in their brief. In addition to the statement on road closures, the Transport Official was given a table of transport modalities and usage for the region. Three datasets were given for this, two surveys of residents and data captured by the urban traffic control centre. These figures were all approximately the same, giving the same sort of relationship between the modalities (car, bicycle, walking, and public transport) just with small perturbations to figures. This was meant as another superfluous dataset, not for main consideration by groups but to add to the noise of the task and to observe if and how it would be incorporated into their process. The multiple sources introduced uncertainty with the issue of negotiating which source to use if they did pick one.

The financial budget was the only data presented to the Finance Officer, this single figure £4 million would provide sufficient budget for groups to cover a substantial part of the region but not all the sites, adding a clear constraint to the problem.

The Health Official was given the previously described vaccine information and data on risk rates, cases, hospitalisations, and deaths. These were presented in tables in the brief, with two sources given for the case, hospital, and death numbers for the region. Each of these sources gave significantly different figures, one from local health service figures, the other from a national virus model projection based on the total population of the region. This introduced another point of uncertainty with multiple sources and a decision point, should participants use this type of data to inform their decisions or understand the scenario more.

The Logistics Official was presented with the table of previously discussed vaccine characteristics, along with the dose supply of each and the medical staff availability (a budget). This added two clear constraints to that part of the task.

The described datasets in this section, across population coverage of sites, facility characteristics, and constraints in different sorts of budget, would push the discussion in the groups into a well-defined trade-off space with a number of pre-determined areas of uncertainty and conflict points. All of this would take place in a time pressured scenario, influenced not only by the allotted task time, but augmented by the volume of information for groups to parse and identify critical information while navigating their decision making process.

Data Quality and The Metadata

The metadata for the datasets in this study were directed by properties of information identified by Matthew West as critical to information quality. Figure 5.25 is a recreated figure from his book, Developing High Quality Data Models (West, 2011). West describes how "...data models play a key role in the information lifecycle through their role in the design of databases and interfaces, and their subsequent maintenance…". As seen in the figure, several clear properties, definition related and value related, can be attributed to a dataset. This structure, combined with the sources of uncertainty identified from Zimmerman (2000) early in section 5.2.4, provided options for data quality metadata to use in the fictional scenario across the datasets generated.

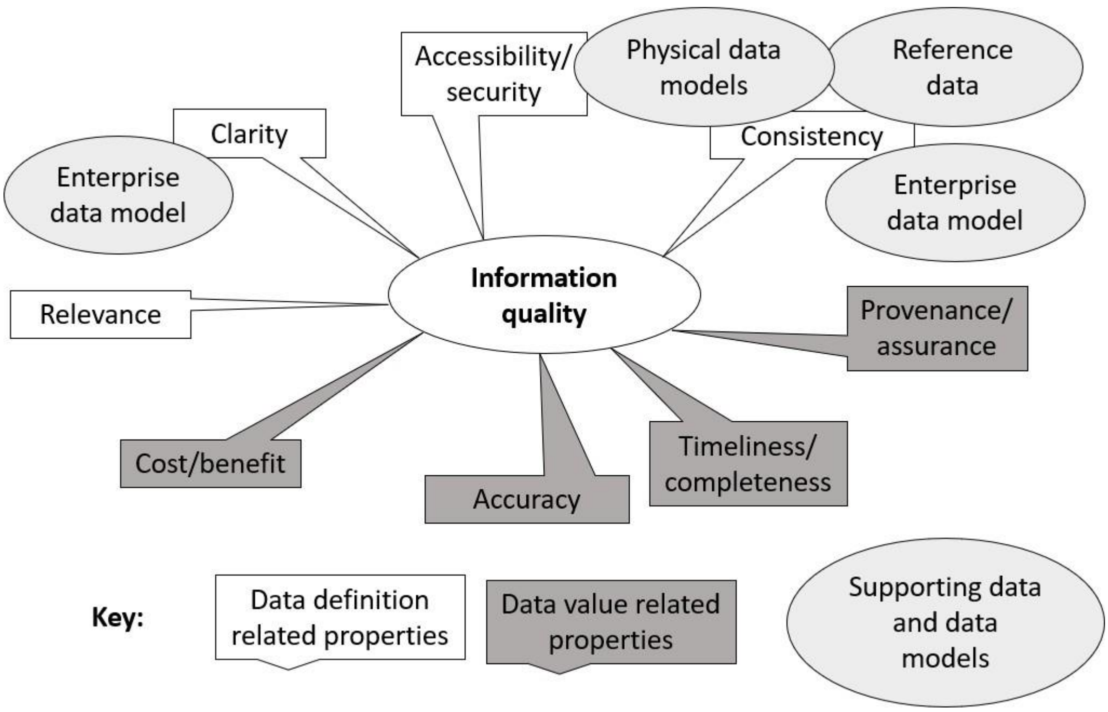


Figure 5.25 Recreation Of Figure From Matthew West Book Developing High Quality Data Models That Shows Properties Of Information Identified As Critical To Information Quality

To contain the problem, and limit complexity of the task and information for these non-expert participants, 3 properties were chosen. These were sources for the datasets (provenance), accuracy, and completeness. All 3 are data value related, they were more easily manipulated, abstractable for one of the tool versions, and clearer for later analysis in the study. Data definition related properties can be seen throughout the datasets and task in the uncertainties and ambiguities described in section 5.2.4, in their clarity and consistency. West describes clarity here as “the meaning of data”, and consistency as “data having the same meaning for different parts of the enterprise”. This would be evident for example in interpreting the accessibility ratings “poor” and “good”, or in the term “nearby” for public transport connections at sites.

The datasets can be split into two categories, those with uniform data quality in this study, and those without. Those without were the datasets for vaccination throughput for both models, staff needed for both models, and the site preparation costs for the 3 vaccine conditions. The remainder were uniform in presented quality. This mattered most when presenting the data in the tool in the abstracted version.

Sources for datasets were generated from grounding in the guidance materials they were based on, for example population figures from the census, throughput numbers from Public Health England, and staffing requirements from WHO vaccination guidance. Completeness and accuracy figures were generated randomly between 65% and 99%, with a weighting towards planned quality levels for each dataset.

The thresholds of abstracted metadata, the traffic lights, weren’t the same across all datasets and types of data within one property. 90% accuracy for one data type isn’t necessarily better than 88% in another, so the first may be rated medium quality and coloured amber, while the latter is rated high and coloured green. The thresholds were a combination of the accuracy and completeness percentages with a trust score for the data source. This allowed some discretion for datasets such as cost of site operation data being rated medium quality despite its high completeness; this is because the figures are generated on a forecast for a pandemic that the region hasn’t experienced before, so there is significant uncertainty in the expected costs associated with the programme.

From this combination score, every dataset was assigned to either high or medium quality. No datasets were assigned to bad quality, but individual data points were given a bad rating to reflect where they fell outside of normal ranges or where data was missing. These anomalous and missing data points were added after the main dataset generation process described in section 2.4.2. The datasets identified above that didn't have uniform data quality were those that conflict points were designed into. Some of these sites in cluster areas, where there were multiple candidate sites in a small area, had data points that were either removed or augmented by whole magnitudes.

For example, staffing requirements for site 12 after this process stated 1700 members of staff would be needed. Similarly, the cost of site preparation for site 22 was just £220. These resemble real datasets that having missing data, or anomalous results that can be the product of data collection, data input, and data handling errors. The sets chosen, some costs, throughputs, and staffing numbers, were selected for sites where a decision would have to be made by groups, so they would have to encounter this missing or anomalous data. This would allow purposeful comparison of responses by groups and management of the data quality across the 3 tool versions. These bad data points were presented as errors in the tool, rather than changes to the actual attributed data in the database. In evaluating proposals, the correct figure for throughput for a 2-pod site would be used but the presented "no data" provides an opportunity to see under time pressure how a group would handle compromised data quality, whether to discard on that basis, ignore the issue, or identify the patterns of pod-dependent variables and estimate the actual number.

Choices for the planned quality levels and score thresholding were based on familiarity and understanding of the data model behind the scenario. Experts such as data brokers familiar with the datasets and the properties in West's figure may have a similar general sense as to the quality of the data they are handling. Further discussion on the thresholding of data quality is discussed in chapters 6 and 7.

This metadata was not present, as discussed in the previous section, in the standard version of the tool. In the abstract metadata version of the tool the additional data quality legend was added to the interface and the data points were coloured appropriately. In the detailed metadata version of the tool, the 3 information properties were presented in the header pop ups for each dataset and in the relevant briefs. This was to avoid cluttering of the interface.

5.3 Procedure

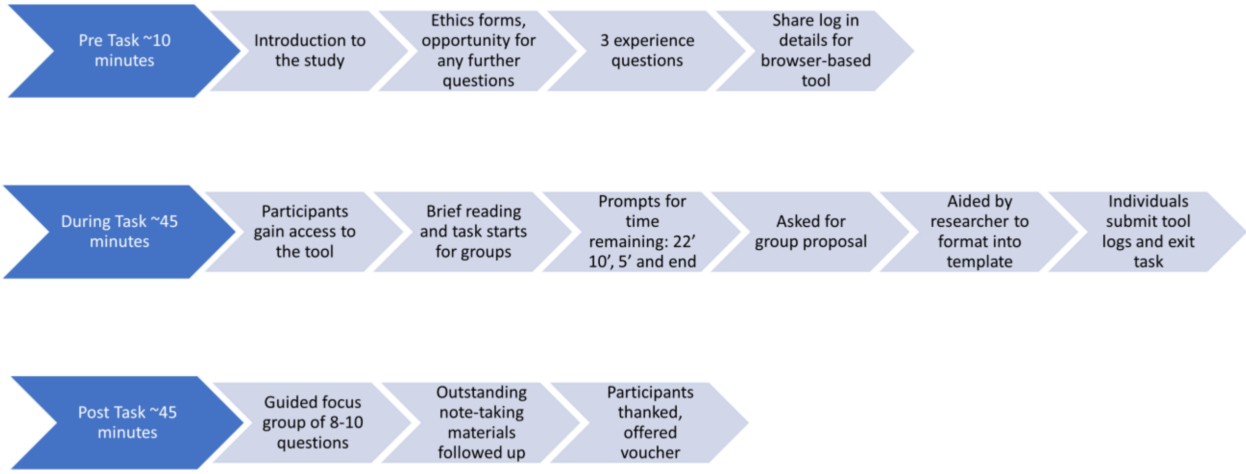


Figure 5.26 Workflow Of Study Procedure Components Across The Three Phases Of Experimental Study

5.3.1 Pre task

Around 10 minutes were allotted for: an introduction to the study to expand on the detail and format given in the recruitment description; asking 3 experience questions; opportunity for any further questions before starting; linking participants to the browser-based tool; and giving them log in details to start the task.

The experience questions asked for self-evaluated ratings from each participant 1-5 (1 low 5 high) of: 1) their technical literacy 2) their experience with GIS (Geographic Information Systems) and 3) their experience with strategy games.

All groups were given prompts regarding the tool they were about to use; the interactions available and header pop ups, and starting actions to begin the task to navigate to the general and role-specific briefs. They were also given a template of a proposal summary table to fill out by the end of the task, see figure 5.27. This template was prepopulated with site information for non-existent sites so that it couldn't be used to complete the actual task.

Site(s) selected	Staffing Model (n/a or 1 or 2)	Medically Trained Staff Assigned	Volunteer Staff Assigned	PhasTech Doses	BioMax Doses
37	2	15	10	25000	15000
41	1	24	17	54000	34000
43	1	22	19	40000	42000
...	...	...	...	...	...

Figure 5.27 Template Of Decision Proposal Provided To Participants Ahead Of Task Phase

5.3.2 During task

Participants were given approximately 45 minutes from the end of the study briefing when they gained access to the tool, through to when they were asked for the group proposal. Prompts for time remaining were given at halfway, 10 minutes remaining, 5 minutes remaining, and time to wrap up the proposal.

The researcher functioned as an observer, muted and with the camera off in the MS Teams meeting, employing an ethnomethodological approach to record interesting behaviours and interactions between group members, the tool, and the task. Communications and interactions to note were mostly guided by the research questions established for this study. These included; emerging techniques of collaboration, sensemaking of the scenario and data, orientation with the tool, and the decision processes. The researcher didn’t proactively provide instruction to the groups, answering only questions that the group couldn’t resolve among themselves or through exploration of the tool, but that could present a barrier to them completing the task. Groups were helped after reaching the end of their task time to fill in the template table using their verbal decisions and notes taken.

5.3.3 Post task

After the proposal summary table was completed, groups moved into the final phase of the study, approximately 45 minutes of a guided focus group.

Groups were asked initially to share the final decision summary table, and to give a brief justification of how they arrived at that combination of sites, staff allocation, and dose distribution. For the remainder of the focus group, participants were asked a series of questions that explored; perception of time scarcity, approach to the decision task, confidence in the final decision and factors that influenced that, satisfaction with individual subtasks, trust in the different data sets, experience using the tool, external materials used during the task, and use of metadata and assessment of data quality during the task. The full list of questions asked to each group is included in appendix B.

Participants were thanked for taking part and were each offered a £15 Amazon voucher for participation, the advertised incentive in the study recruitment materials.

5.4 Data recording

The following data was collected during the task and focus group phases:

- Tool logs of every interactable button click by each participant, timestamped to local time (to the participant) and tagged with the button clicked. Outputted by clicking of the submit button at the end of the task was a list from each participant of each button and all associated timestamps. E.g., Operation Tab Counter: 16:05:41, 16:05:47, 16:06:16, 16:16:45, 16:19:24, 16:20:04, 16:20:50, 16:26:58, 16:48:42.
- Recordings of MS Teams calls.
- Summary proposal tables from each group as shown in the procedure section above.
- Artefacts from each group from working outside of MS Teams or the browser-based tool, this included: word processor documents, MS Excel files, notepad text files, screenshots from these programs, and photographs of handwritten notes.
- Observation notes from the researcher for each group during their task phase.
- Answers to pre task questions and focus group discussion were captured by the MS Teams recording.

Handling and analysis of these data are covered in the next section.

5.5 Data treatment and analysis procedure

This section explains how each of the sets of data recorded during the study were handled and analysed.

Tool logs

Logs for each participant were exported to Microsoft Excel and put into query-able tables.

Counts were calculated for each button for each participant, and then aggregated by group and by role, with summary statistics for each of these.

For each participant, clicks were sequenced chronologically, recreating the order of interactions with the tool for each individual. The design of the tool meant that 1 of 5 data groupings was always visible once the task had started, corresponding to the active data tab described in point 2 of figure 5.7 earlier in this chapter. The tab that was active was allocated as being in focus for the purpose of analysis. The sequence of clicks was reduced, still in chronological order, to the buttons for those 5 tabs. Differences in timestamps for each click in the interaction sequence were computed, with source and destination tabs, assigning the difference, the focus time, to the source tab. For example, the sequence "19:20:15, Population. 19:20:18, Brief. 19:21.23, Cost." would result in assigned focus times of 00:00:03, Population and 00:01:05, Brief. This tab focus time calculation was repeated for all participants and produced individual focus time summary totals that were aggregated by group and by role in the same way as the click counts. In addition, these raw times for tab focus were converted into percentages at the participant, role, and group level.

Focus changes were also calculated with the focus time, this was the number of distinct data group tab clicks. Participant, group, and role summaries were aggregated.

Proposal summaries and outcomes

Summaries were taken from a mixture of submitted artefacts and extracted from transcripts where groups gave their table verbally.

For each group, proposals were translated into a common format that listed each site selected, then for each site; which staffing model was being used, number of medically trained staff assigned, number of volunteer staff assigned, number of PhasTech doses assigned, and number of BioMax doses assigned. A series of checks was carried out on predefined constraints. These included checking proposals against; medically trained staff budget caps, volunteer staff caps and volunteer to medically trained staff ratio check for each site (where exceeding 1:1 vaccinations were scaled by a factor of 75% to reflect the one week delay advertised to the groups in their brief for volunteer training), dose allocations for both vaccines against initial availability, and site usability for the two with road closures (if used in proposals the sites were discarded before continuing outcome calculations).

Population reached/serviced by each selected site was calculated for each age band and then summed for the total population 16+ reached. This catchment figure was calculated using a scaled equation of the population from the master population datasheet (see population figures section of the design of data earlier in this chapter) for both travel distance 1 and 2. Figure 5.28 below shows how this figure was calculated.

$$\text{Population serviceable by site} = \left(\text{Population (age band, travel distance 1)} \times \text{Vaccine hesitancy (age band, travel distance 1)}\right) + \left(\text{Population (age band, travel distance 2)} \times \text{Vaccine hesitancy (age band, travel distance 2)}\right)$$

Equation 5.1 Equation Used To Calculate Population Serviced By Candidate Vaccination Sites In Study Data Design

Vaccine hesitancy was used as a scaling factor for population coverage, and was a function of the age band and the travel distance. Table 5.1 shows the relationship between these variables. Hesitancy figures were based on those exhibited across at least 8 categories by ONS data for Coronavirus vaccine surveys (‘Coronavirus and Vaccine Hesitancy, Great Britain - Office for National Statistics’, n.d.). For the purpose of this study, a single hesitancy figure was applied to each age band, no other demographics were used in the calculation as no other demographics were offered to participants as part of the task. It was also modelled that with the increased travel distance there would be greater hesitancy to travel for a vaccination within the whole population. These hesitancy figures were given as a percentage of the population that would travel for the vaccine. So, a hesitancy of 5% in 50-69 year olds at travel distance 1 would be interpreted as 95% in the table and calculations.

	Vaccine Hesitancy Scaling Factors			
	16-29	30-49	50-69	70+
Travel Distance 1	83%	87%	95%	97%
Travel Distance 2	73%	77%	85%	87%

Table 5.1 Vaccine Hesitancy Scaling Factors Used By Travel Distance And Population Age Group In Experimental Study Data Design Phase

Scaling was introduced for overlapping sites at travel distance 1 and 2. Population was assumed as having uniform density across the catchment area of a site. The population in the overlap of two site catchment areas was estimated, the overlap area was bisected, and each half attributed to its nearest site. Figure 5.29 illustrates this method for an example of two selected sites with overlapping travel distances.

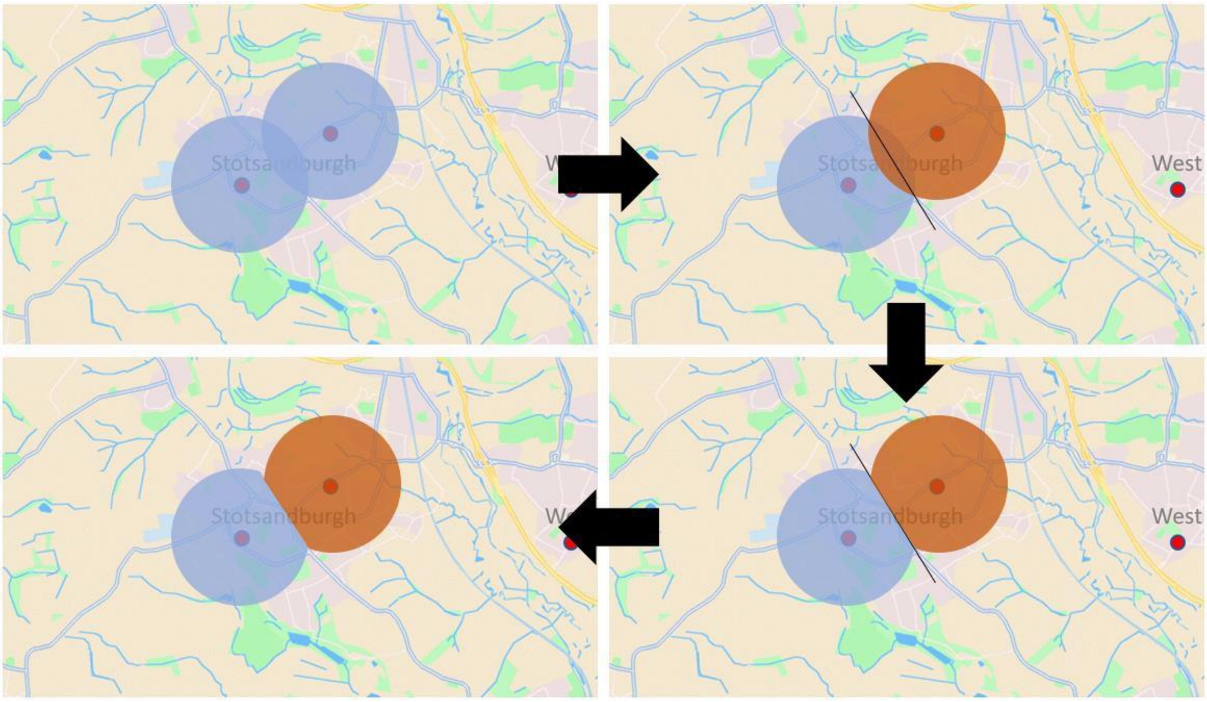


Figure 5.28 Workflow Of Candidate Site Catchment Area Overlap Population Division In Data Design Phase

The purpose of this study wasn't to develop or test accuracy of population modelling, vaccine hesitancy, or vaccination delivery models. The approach outlined above for proposal outcome calculations, consistent across all groups, enabled the decisions and subsequent outcomes to be compared across groups and tool versions.

Dose distribution was aggregated across sites for both vaccines used.

Maximum vaccination throughputs for a month of site operation were calculated based on the model of staffing chosen and figures presented to the participants.

To calculate the distribution of vaccine doses at each site, equal distribution across each target age band was assumed as no discussion was had, or prompt given to groups for phasing of vaccine priority groups, only risk factors. PhasTech was distributed evenly across all age bands. BioMax across just the 50-69 and 70+ bands as per vaccine characteristics given to participants. The number of people vaccinated at each site was the lowest of two numbers, the population in that age band or the vaccine doses available at that site for each age band. Where doses exceeded the eligible population for that site, the difference contributed to a summed wasted dose value.

Total costs were summed for set up, operation, and combined for each site proposed.

A table of sites selected by each group and a breakdown of the frequency each site was selected and each facility type was selected was created. This listed the site number, facility type, times a group picked the site, the percentage of groups using that site in their proposal, and for each site the list of groups that used it.

From the above datasets, a summary table was created containing the following as outcomes to each group proposal: group number, sites selected, number of sites, cost of set up, cost of operating sites, total cost, budget left, medically trained staff used, volunteer staff used, BioMax doses allocated, PhasTech doses allocated, total doses allocated, vaccinated population for each age band, a total vaccination delivery for population 16+, and wasted doses. An additional table with these dataset headings was created by aggregating the groups by the tool version they used and averaging their decision outcomes.

Artefacts

Artefacts from each participant were collected, these were from any working outside of MS Teams or the browser-based tool, this included: word processor documents, MS Excel files, notepad text files, and handwritten notes. These were anonymised and key features summarised to assist understanding of the decision making process, use of the tool, and to augment interpretation of thematic analysis in later stages.

Observation notes from group task phases

These notes by the researcher were aggregated and themed to assist with thematic analysis of transcripts, and to direct analysis to interactions or events of particular interest that occurred for each group.

Recordings of MS Teams calls

Audio was transcribed and anonymised. Transcripts were then thematically analysed, firstly with in vivo coding guided by the research questions for the study and the observations made during the task phases. Deductive coding then generated a richer set of data extracts based around the emergent themes of the inductive process.

Answers to pre task questions and focus group discussion

These were both captured by the MS Teams recording. Pre task questions were lifted into tables of scores for each participant. For quantitative questions in the focus group portion of the study, scores were similarly lifted into tables of scores for each participant; these were the questions that asked for scores on the confidence in the decision the groups made, and the trust in various datasets presented in the task. The remainder of the focus group discussion was also included in the thematic analysis of the transcripts.

The pre questions, self-evaluated scores of technical literacy, experience with GIS tools, and strategy game experience, were sorted by group and roles, and subsequently by tool version used, to inform interpretation of the decision outcomes and process. Averages across the groupings were tabulated. A whole study population average was also taken for comparison for the three questions.

The confidence scores for each participant were grouped in a similar way, by study group and by tool version used. Averages were also calculated for these.

Trust scores for the 10 data groupings given to the participants were aggregated in a few ways. Averages of trust for each data grouping were calculated across all participants, across groups, and across tool versions used. Summary trust scores were also calculated for all data groups combined across each study group and across each tool version used.

The next chapter will present the results of the analysis outlined and discuss the findings of the study.

6. Experimental Study Findings and Discussion

6.1 Results

This section will present the results of the experimental study described in chapter 5. These include:

- Decision outcome summaries and statistics for each group, the proposals and effectiveness of them
- Summary statistics from pre and post task focus group questions, trust and confidence scores
- Main themes from thematic analysis of focus groups
- Main themes from thematic analysis and observations of interactions during the decision process
- Summary statistics of the tool interaction captured by the interface
- Artefacts of the decision process, materials used outside of the tool by participants

6.1.1 Decision outcome summaries and statistics

The proposals for each group are presented below in table 6.1, grouped by their tool versions. One group from each metadata abstraction made a constraint error in their proposals. Red figures in group 7's volunteer staffing, and group 2 and 3's vaccine doses indicate proposal dimensions that exceeded the constraints of the task. Group 7 exceeded the ratio of volunteer staff to medically trained staff allocated at two sites and so would face a one-week delay of opening those sites in calculations for their outcomes. The dose proposals for group 2 and 3 exceeded the supplies available, so the maximum within budget was used in outcome calculations. Site 17, highlighted in red for a site selected by group 5 and 9, indicates two groups that selected a site that couldn't operate due to a road closure shared in the Transport Official brief.

	Group	Sites	# of sites	Med. Staff	Vol. Staff	BioMax	PhasTech	Total Doses
Non Meta	1	1,5,6,9,13,14,15,18,20,22,23	11	239	236	123,428	74,055	197,483
	4	3,7,8,11,15,21,25	7	168	155	124,999	74,998	199,997
	7	3,7,10,13,14,15,19,22,25	9	196	239	124,998	74,997	199,995
	Average		9.0	201	210	124,475	74,683	199,158
Abstract Meta	2	3,7,11,14,15,18,21	7	243	127	104,000	98,500	202,500
	5	1,5,6,9,14,16,17,18,20,21,22	11	234	216	124,999	74,995	199,994
	8	1,3,5,7,9,15,20,21,22,25	10	221	111	125,000	75,000	200,000
	Average		9.3	233	151	118,000	82,832	200,831
Detail Meta	3	5,9,14,18,21	5	193	0	155,000	90,000	245,000
	6	5,6,13,14,18,20,22	7	99	88	124,999	74,998	199,997
	9	5,6,9,13,15,17,21	7	139	136	125,000	75,000	200,000
	Average		6.3	144	75	135,000	79,999	214,999

Table 6.1 Group Proposals From Experimental Study

Non metadata and abstract metadata groups chose, on average, more sites in their proposal during the same task time, with detailed metadata groups choosing much smaller proposals. Staff allocation reflected the number of sites chosen, fewer sites meant lower staff requirements so detailed metadata groups used less of their medically trained staff budget and similarly the volunteers to work with them. Group 3 neglected to use any volunteer staff. Most groups distributed their doses using the same formula as they were reaching their task time limit completing the rest of the decision and table. This allocation split the stated supply of doses for each vaccine evenly across all their selected sites. The exceptions were group 2 and 3 that built upwards from a site level allocation rather than downwards from a supply level allocation. These estimated the supply they could afford for a site, then multiplied up for each site chosen.

The impact of exceeding constraints for the groups were as follows: Group 2 approximately 2,500 fewer doses were distributed than proposed, Group 3 approximately 45,000 doses weren't distributed as proposed, and Group 7's staff training delay cost around 8,100 vaccinations.

Table 6.2 shows the outcomes of the proposals summarised in table 6.1, and some measures of the effectiveness, again these are grouped by the abstraction level of metadata that the groups were given. In the same way that non metadata groups chose similar numbers of sites to abstract metadata groups, the costs of their proposals came out similarly close. These 6 groups shared the top 6 proposals on use of budget split evenly, with a notable performance by Group 1 to leave less than £60,000 in their budget. Detailed metadata groups underspent the other groups significantly, with Group 3 spending less than half their budget. This is in part proportional to the number of sites that groups chose in their proposal.

The important outcome for comparison of groups was the success of their vaccination programmes provided they were within constraints such as budget. Table 6.2 again shows how the detailed metadata groups were outperformed by the groups in the other two tool versions, by an order of magnitude in some parts, with the top 6 spots split across non metadata and abstract metadata groups. Group 1 demonstrates a notable performance again on these outcomes with the highest vaccination reach outside of the 16-29 age bands, fewest wasted doses as a result, and the greatest percentage of over 16s in the region vaccinated. A suggestion as to why this group performed so well is discussed later in this chapter.

	Group	Costs				Vaccinated						
		Preparation	Operation	Total Cost	Budget Left	16-29	30-49	50-69	70+	Total 16+	Wasted Doses	% 16+
Non Meta	1	£212,000	£3,728,712	£3,940,712	£59,288	30,628	39,343	87,802	28,548	186,320	11,163	62%
	4	£192,500	£3,226,770	£3,419,270	£580,730	33,268	36,345	77,953	23,022	170,589	29,408	57%
	7	£152,500	£3,517,368	£3,669,868	£330,132	29,114	34,316	80,792	27,106	171,327	28,668	57%
	Average	£185,667	£3,490,950	£3,676,617	£323,383	31,003	36,668	82,182	26,225	176,078	23,080	59%
Abstract Meta	2	£85,500	£2,600,286	£2,685,786	£1,314,214	25,808	29,717	71,251	25,232	152,008	50,492	51%
	5	£208,000	£3,532,464	£3,740,464	£259,536	28,168	35,708	79,404	24,553	167,833	32,161	56%
	8	£197,500	£3,396,600	£3,594,100	£405,900	34,895	38,388	82,276	21,615	177,174	22,826	59%
	Average	£163,667	£3,176,450	£3,340,117	£659,883	29,623	34,604	77,644	23,800	165,672	35,160	55%
Detail Meta	3	£80,000	£1,660,560	£1,740,560	£2,259,440	21,468	25,978	57,534	19,596	124,575	120,425	42%
	6	£156,000	£1,868,130	£2,024,130	£1,975,870	19,158	29,193	67,712	23,629	139,692	60,305	47%
	9	£156,000	£2,158,728	£2,314,728	£1,685,272	25,211	26,378	57,384	16,233	125,206	74,794	42%
	Average	£130,667	£1,895,806	£2,026,473	£1,973,527	21,946	27,183	60,877	19,819	129,824	85,175	43%

Table 6.2 Outcomes Of Group Proposals Calculated

Table 6.3 shows an aggregation of the sites chosen by each group, and their popularity within and between tool versions. As with table 6.1, and for the remainder of this chapter, where sites 12 and 17 are highlighted red is to indicate they were unusable sites due to road closures that were shared with the participants. No groups chose site 12, only 2 chose site 17. In this format the level of agreement can be seen within and between metadata abstractions. Across all versions, the highest level of agreement was from 6 groups choosing the same sites: 5, 14, 15, and 21. Each tool version had a different site that all 3 of the respective groups chose. For the non metadata this was site 15, for abstracted metadata this was 21, and for detailed metadata this was site 5. Some sites were only avoided by all groups in just one abstraction level, such as sites 1 and 25 for the detailed metadata groups, and site 13 for the abstracted metadata group.

Group and Sites Selected												
Sites				Non Meta			Abstract Meta			Detail Meta		
Site #	Facility Type	Times Picked	% Groups	1	7	4	2	5	8	3	6	9
1	Existing healthcare infrastructure	3	33%	1				1	1			
2	Pharmacy	0	0%									
3	Community centre	4	44%		3	3	3		3			
4	Pharmacy	0	0%									
5	Community centre	6	67%	5				5	5	5	5	5
6	Pharmacy	4	44%	6				6			6	6
7	Existing healthcare infrastructure	4	44%		7	7	7		7			
8	Sports facility	1	11%			8						
9	Existing healthcare infrastructure	5	56%	9				9	9	9		9
10	Community centre	1	11%		10							
11	Sports facility	2	22%			11	11					
12	Pharmacy	0	0%									
13	Pharmacy	4	44%	13	13						13	13
14	Community centre	6	67%	14	14		14	14		14	14	
15	Community centre	6	67%	15	15	15	15		15			15
16	Pharmacy	1	11%					16				
17	Community centre	2	22%					17				17
18	Existing healthcare infrastructure	5	56%	18			18	18		18	18	
19	Community centre	1	11%		19							
20	Pharmacy	4	44%	20				20	20		20	
21	Pharmacy	6	67%			21	21	21	21	21		21
22	Community centre	5	56%	22	22			22	22		22	
23	Community centre	1	11%	23								
24	Sports facility	0	0%									
25	Sports facility	3	33%		25	25			25			
			# of sites	**11**	**7**	**9**	**7**	**11**	**10**	**5**	**7**	**7**

Table 6.3 Aggregation Of Sites Chosen As Part Of Each Group Proposal

Just 4 sites of the 25 candidates weren't chosen by any of the groups, these are highlighted in table 6.4. Notably 3 of these are pharmacies, which made up 8 out of the 25 candidate sites. 9 had been community centres. There were 4 existing healthcare infrastructure sites available, and 4 sports facilities.

Sites	Facility Type	Times Picked	% groups
2	Pharmacy	0	0%
4	Pharmacy	0	0%
12	Pharmacy	0	0%
24	Sports facility	0	0%

Table 6.4 Summary Of Sites Not Selected By Any Group During Task

7 sites were popular with more than half the groups, this time mostly made up of community centres and existing healthcare infrastructure as shown in table 6.5.

Sites	Facility Type	Times Picked	% groups
5	Community centre	6	67%
14	Community centre	6	67%
15	Community centre	6	67%
21	Pharmacy	6	67%
9	Existing healthcare infrastructure	5	56%
18	Existing healthcare infrastructure	5	56%
22	Community centre	5	56%

Table 6.5 Summary Of Top Sites Selected By Groups During Task

As described in chapter 5 in the study and data design, a number of the sites had low quality data built into the datasets to introduce clearer opportunities for decision conflicts and group assessment and navigation of data quality. The data quality was lowered for sites 6, 14, 18, and 24 by removing vaccination throughput data in the operations tab and displaying “No Data”. The remainder of the sites in table 6.6 had data points distorted by a couple of orders of magnitude, for example a preparation cost for site 22 was altered from

Sites		Times chosen		
Site #	Cause of low quality data	Non Meta	Abstract Meta	Detail Meta
4	Errors in cost data	0	0	0
13	Errors in cost data	2	0	2
22	Errors in cost data	2	2	1
24	Errors in cost data	0	0	0
	Total	4	2	3
6	Missing throughput data	1	1	2
14	Missing throughput data	2	2	2
18	Missing throughput data	1	2	2
24	Missing throughput data	0	0	0
	Total	4	5	6
4	Errors in staff requirement data	0	0	0
12	Errors in staff requirement data	0	0	0
19	Errors in staff requirement data	1	0	0
	Total	1	0	0
All	All Above	9	7	9

Table 6.6 Summary Of Sites Affected By Low Quality Data

£22,000 to £220, and a staff requirement figure for site 12 was altered from 17 to 1,700. Table 6.6 shows the number of instances that groups from each tool version selected one of the sites impacted by this low quality data as part of their proposal. For sites with “No Data” values in their datasets that were used in proposals, at least 1 group from each metadata abstraction chose the site. For sites with erroneous data in staffing, only 1 site was chosen, and this was by a non metadata group. Sites with erroneous cost data were most commonly used by the non metadata groups.

6.1.2 Summary statistics from pre and post task questions

Before starting the study, participants were each asked to give a self-evaluated rating from 1-5 on their technical literacy, their level of experience with GIS, and their experience with strategy games. Table 6.7 presents the group averages for each of these dimensions, and the overall averages for the metadata abstraction groupings and the overall study. All groups evaluated themselves with similar experience levels with GIS on average. This is expected with the sampling method, domain experts weren’t targeted in recruitment.

		Group averages		
		Tech Literacy	**GIS Exp**	**Strat Game Exp**
Non Meta	Group 1	5.0	1.0	3.8
	Group 4	3.8	1.8	3.5
	Group 7	4.3	1.8	4.3
	Average	4.3	1.5	3.8
Abstract Meta	Group 2	2.5	2.3	2.5
	Group 5	4.0	2.0	3.5
	Group 8	3.5	1.5	2.8
	Average	3.3	1.9	2.9
Detail Meta	Group 3	3.5	1.3	3.0
	Group 6	3.5	2.0	1.5
	Group 9	4.0	1.3	2.8
	Average	3.7	1.5	2.4
All participants		3.8	1.6	3.1

Table 6.7 Group Scores For Pre-Task Questions On Tech Literacy, GIS Experience, And Strategy Game Experience

A small number of individual participants rated themselves a significant amount above the average, as explored in the next figures in this section. Greater differences in groups and in tool version groupings were seen in the strategy game experience and technical literacies of participants. Non metadata groups had higher technical literacy ratings on average, with Group 1 all scoring themselves as 5/5. For strategy game experience, the gap from the non metadata groups were much higher.

Figures 6.1, 6.2, and 6.3 plot the distribution of these ratings within groups within metadata abstractions.

For technical literacy, the lowest scores of 3/5 are the exceptions within the non metadata population. Abstracted metadata participants showed the same variation in scores but a point lower. Detailed metadata participants showed the greatest variability in technical literacy scores for figure 6.1 with one exceptionally high and low score.

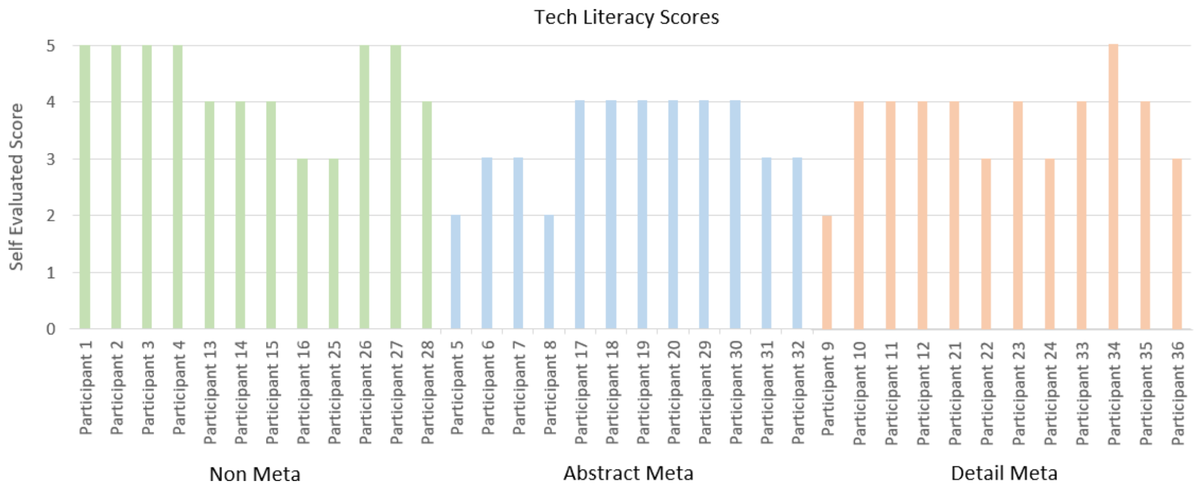


Figure 6.1 Graphing Of Tech Literacy Scores For All Participants By Group

GIS experience shows a mostly level rating across the study population in figure 6.2 with exceptions for higher ratings, mostly in the abstracted metadata groups. Ratings of 1 were attributed by those who have never or barely heard of GIS, while those scoring 4 explained that they did some work on a weekly basis at their job that involved GIS.

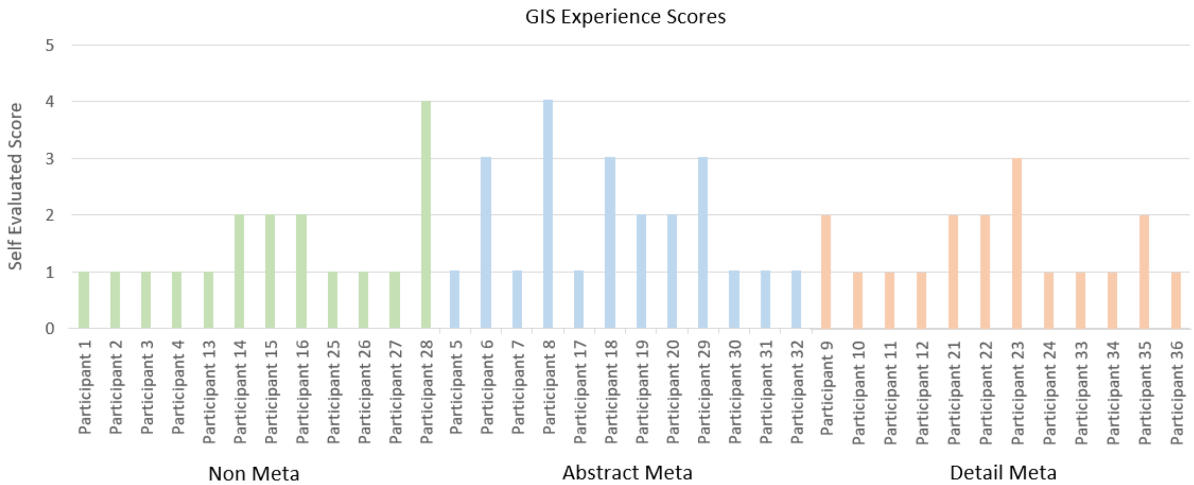


Figure 6.2 Graphing Of GIS Experience Scores For All Participants By Group

Strategy game experience ratings in figure 6.3 show the most variable set of ratings for the 3 dimensions. Non metadata groups still showed a higher level of experience on this, with just 1 participant below 3/5. Conversely, detailed metadata groups were the least experienced in this regard with just 1 participant recording above 3/5.

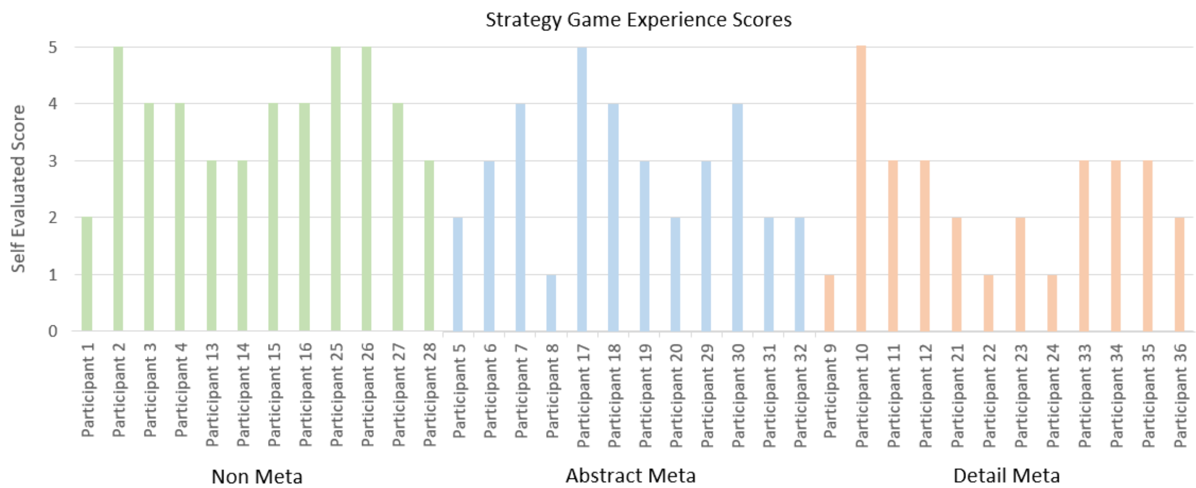


Figure 6.3 Graphing Of Strategy Game Experience Scores For All Participants By Group

After the task time was over, participants individually scored their confidence in the proposal that the group had arrived at, scoring between 1-10. These are presented in table 6.8. Group 1 were most confident in their final decision, group 3 the least. Non metadata groups recorded significantly lower confidence scores. Including group 9 in the tool version averages, the non metadata groups were still considerably less confident in their decisions that the groups from the non metadata and abstracted metadata data versions.

Group		Proposal Confidence
Non Meta	Group 1	7.25
	Group 4	6.50
	Group 7	6.25
	Average	6.67
Abstract Meta	Group 2	6.00
	Group 5	5.75
	Group 8	6.25
	Average	6.00
Detail Meta	Group 3	3.25
	Group 6	3.50
	Group 9	6.00
	Average	4.25

Table 6.8 Group Decision Confidence Scores

Later in the focus groups, participants were asked to score 10 datasets that had been presented to them in the decision support tool, this time rating the level of trust they had in the dataset on a scale from 1-10. The group averages for these data trust scores are presented in table 6.9. Averages were calculated within groups, within metadata abstraction levels, and within datasets. These scores are also plotted in figure 6.4 as the patterns of trust can be seen more clearly.

Group		Trust score for each data set										
		Population Bands	Vaccine Throughput	Staff Needed	Min. Medical Staff	Max. Volunteers	Preparation Cost	Operation Cost	Car Parking	Nearby Bus Stops	Accessibility	All Data
Non Meta	Group 1	6.75	6.00	7.25	7.00	7.25	4.00	4.25	8.25	7.00	6.75	6.45
	Group 4	7.25	6.75	7.50	5.00	4.50	7.00	7.50	7.50	9.75	9.25	7.20
	Group 7	7.50	5.25	8.00	8.25	7.00	7.25	5.75	8.25	9.75	8.25	7.53
	Average	7.17	6.00	7.58	6.75	6.25	6.08	5.83	8.00	8.83	8.08	7.06
Abstract Meta	Group 2	8.25	7.75	7.75	8.00	8.00	7.75	7.75	8.50	8.25	7.75	7.98
	Group 5	6.50	6.25	6.75	6.00	8.00	6.75	6.75	7.25	9.00	6.50	6.98
	Group 8	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
	Average	8.25	8.00	8.17	8.00	8.67	8.17	8.17	8.58	9.08	8.08	8.32
Detail Meta	Group 3	6.25	6.75	5.00	2.75	2.75	7.00	6.75	8.75	9.00	6.00	6.10
	Group 6	8.25	6.00	6.00	6.75	5.50	5.75	7.00	8.00	7.25	5.75	6.63
	Group 9	6.25	4.25	7.75	4.50	4.75	4.75	6.25	8.75	6.25	3.50	5.70
	Average	6.92	5.67	6.25	4.67	4.33	5.83	6.67	8.50	7.50	5.08	6.14
All versions		7.44	6.56	7.33	6.47	6.42	6.69	6.89	8.36	8.47	7.08	7.17

Table 6.9 Group Trust Scores For All 10 Datasets

For most datasets, groups from the detailed metadata version of the tool had the lowest trust. The trust levels of the non metadata groups tracks relatively closely the average trust scores of the whole study population across the 10 datasets. Groups presented with the abstracted metadata, the traffic light ratings of data quality for each dataset, had the highest trust in the data, markedly higher than the other groups except most notably for car parking data and nearby bus stop data for the sites. These two datasets, both in the transport tab of the tool, saw the greatest level of agreement across the 9 groups in the study. Car parking saw average trust scores within 0.58 of each other. Across the datasets, the trust scores for non metadata groups were more often closer to those of the detailed metadata group than the abstracted groups.

Full pre and post task experience, confidence, and trust scores are included in appendix F.

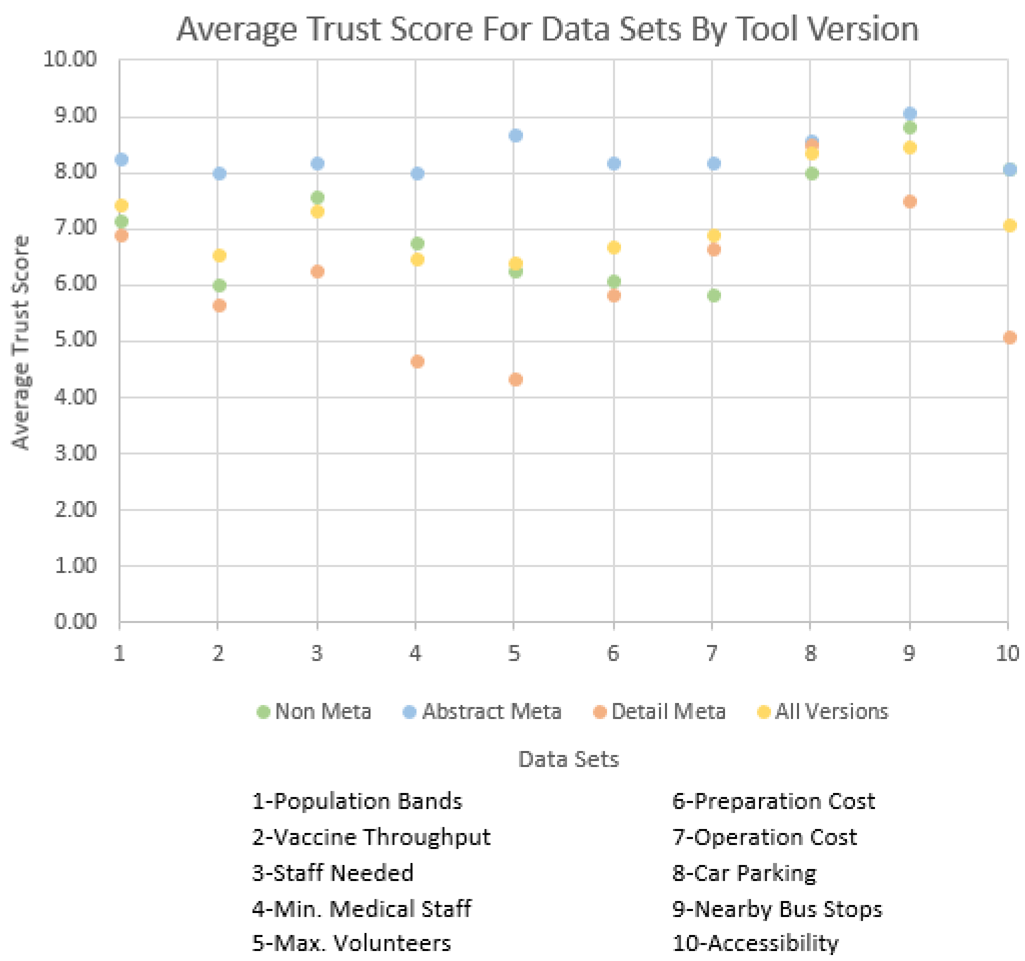


Figure 6.4 Plot Of Average Trust Scores For Datasets Split By Metadata Abstraction

6.1.3 Themes from thematic analysis of focus groups

This subsection presents the themes of discussion from the focus groups that followed the task phase for each group. The themes follow the line of questioning from the focus groups that was described in chapter 5, with findings emerging from there, as opposed to the emergent theme approach in the next subsection used for the unstructured task phase.

Two key themes, data trust and proposal confidence were used, with subthemes around metadata (within data trust), time scarcity and desires to improve confidence (within the proposal confidence theme). Beyond these two, tool feature desires and external programme/material use were auxiliary themes that don't form clear subthemes, instead run across each other and the two key themes.

Data Trust

The discussions after scoring trust of each datasets revealed 5 factors that strongly influenced their level of trust. These were:

- Perception of data sources
- Experience or familiarity with the data type
- Perception of ease of accurate data collection
- Perceptions of ability to accurately predict the data
- Perceptions of objectively correct data

Sources and their credibility

For many participants the presence or appearance of a source instilled some trust in the validity of data. These sources were, even to non-experts, known entities, for example,

P35: "I trust the World Health organising - the WHO column"

P2: "I would personally believe the census is relatively good data to go off of. "

P24: "You know you asked us all about reliability of the data though, I was influenced when you were asking me about whether I thought the data was reliable, *by remembering that there'd been like mentioning of sourcing of data, that kind of made me think that the data we were given was reliable."*

P33: "Just the fact it was— Confirmation that it hasn't been made up, basically. Well, it could've been made up but it wasn't just made up."

The sources didn't need to be the assigned one in the data design stage of the study, some participants interpreted their own sources for the data they were given, attributing in some cases the data to the sites they were associated with and characterised them,

P10: "Yes, I think I personally trust the existing health infrastructure and the pharmacies more than the community centres and the sports facilities in terms of medical output, but not so much in terms of – sports facilities probably have better sort of transport and that sort of thing, accessibility because that's what they're more used for."

Some participants weren't convinced by data having a source, but would want to know more about the source for all the data in one of the sets, in this case it was accessibility ratings for sites,

P11: "It depends on whether the same person's decided they're all good or poor. Without knowing that, yes I would make it 6 across the board."

These extracts demonstrated an ease with which participants assumed validity and trusted data that were reportedly from sources they had heard of, and trusted, or could believe were appropriate and trustworthy sources.

Familiarity with data types

Trust for some participants was guided by their lived experience, whether in a professional capacity, or in anecdotal manners. Many participants were influenced in this way when discussing trust in the cost figures for operation and preparation of sites. Few groups could provide experiences of projects of a similar scale to the fictional scenario that had run to budget, and therefore they were hesitant to trust any cost figures presented.

P2: "So I would say my prejudice – mine potentially comes from previous prejudice of generally bureaucratic systems causing – like costing more than people actually realise and stuff like that…in the real world."

Commenting in a discussion on staff requirement and minimum staffing levels provided in the support tool, participant 36 struggled to trust the numbers in the scenario,

P36: "I was going to say, if it's Britain, the NHS are always understaffed."

Feelings such as the above indicate that some datasets will have more strongly established pre-existing trust levels for individuals based on their experience and domains of work, and may require more explicit efforts to alter that bias. This will be significantly influenced by the experiences of group members that are being studied or supported, and would be expected to present a greater hurdle in expert groups with more familiarity with data types and likely stronger prejudices.

Perception of ease of data collection

For some of the datasets, a lot of the data trust discussions centred around the perceptions of how easily someone could count, calculate, or collect the data that was being presented. A recurring theme was that participants had higher trust in sets that they thought were easily verified, such as counting car parking spaces and finding bus stops.

Participant 17 and 18 on bus stops,

P17: " I was similar to [Participant 18]. The stuff you can go and count now, I'd have faith in."

P28: " 10, I don't know how you can really get that wrong."

Participant 13 and 33 on car parking,

P13: "The thing is, the number of car parking spaces and bus stops, those should be pretty easy to add up a few car parking spaces, it's unlikely to be wrong….Yeah. Whereas something like population could change quite a lot, in terms of like who's covered under what, by which sites."

P33: " Yeah, nine. If you go out, you can count how many spaces you have in a car park (laughs)."

These two datasets were the most agreed upon quantitatively as seen in section 6.1.2, but also in the qualitative justification of the trust levels.

Participant 5 (on staffing numbers) and 15 (on site costs) explained how they thought some other datasets that may not be easily counted outside, could be easily calculated, and so were trusting of the data presented,

P5: "Oh yeah, well I don't think— Honestly, I think that's also a nine. I think with things like this, you can very easily understand how many people are required to do a certain thing."

P15: "I think that operation running costs tend to be quite consistent generally. Because it's not like you're – I mean, there's PPE, PPE is probably the biggest variable cost in terms of – what anyone would be buying. But otherwise, I mean, electricity, water, those kinds of things all have set rates. Insurance is a set cost."

Similar to the familiarity some group members may have with a data type, the perceived ease calculating/collecting a dataset, how hard could it be to get it wrong, lowers the burden of trust building that the decision support tool needs to assist in. The more in agreement people are likely to be in how easily a dataset could be collected, the lower that burden.

Perception of prediction accuracy

These excerpts are related to the previous subsection, an ease of gathering a dataset, but purposefully split to show the difference in sentiment towards predicted data over static and historic datasets.

Participant 18 rated the vaccination throughput projections as 5/10,

P18: "I was a bit sceptical about the whole vaccination thing. It was like, this feels like it's the very start of it, how do we know how many vaccinations we can give and *how many are going to be wasted and how many people we can do there. I was a bit sceptical about that data."*

While participant 17 interpreted the staffing data as projections, and scored the vaccination throughput and volunteer requirements as 6/10 each,

> *P17: "I mean, a lot of those datasets are speculative. I imagine those people have a good idea of what they're talking about, but at the end of the day you don't know exactly how many volunteers you're going to need, how many vaccines you can roll out."*

Discussions showed a link to the previous subsection on participants abilities to ground truth and verify that dataset. The predicted datasets, particularly around an uncommon event such as a pandemic, seemed to them more speculative and harder to check. These datasets could really only be verified in retrospect, evaluated after the fact such as if throughput levels predicted matched those that were hit, or whether staffing levels were sufficient in reality.

Perception of data being objectively correct

Some participants had clear trust in datasets they considered as objectively correct. Beyond seeing them as easy data types to verify, they saw these as indisputable.

> *P8: "Oh, I'd probably say— I feel like costs are quite reliable, like they're not kind of wishy-washy. So I'd probably say ten."*

> *P7: "Car parking, probably a ten because it's pretty black and white."*

> *P22: "Yeah, I didn't look at it, but car parking you can't really get wrong, can you, so I'll put a 7. It's easy to count, it's pretty set in stone."*

Participant 18 combined their trust in a source, the city council, with their perception of the datasets, placing high trust in population and transport data,

> *P18: "I think for me I trusted stuff like the population and the transport, the kind of stuff a city council is going to know. They're going to know who lives where and*

they're going to know where their buses are, and they're going to know where their car parks are."

Trust building behaviours

Participants demonstrated how they established their trust levels in some datasets. This often meant either validating expectations or observing comparative data. This meant that participants had some expectations of what data they may be unfamiliar with would look like, such as cost and population data being presented as ranges rather than single figures. Where the datasets reflected these expectations, the participants placed greater trust in the data.

P19: "I just kind of went, that one, that number's bigger than that, I trust it to be bigger than that, but I don't trust it to be bang on."

Presenting data in a way that is transparent about the uncertainty, such as ranges, helped participants place more trust in that set.

P5: "I think because there wasn't a good range, because it gave quite a bit of range, I think you're more likely to trust it because you know that they're— You know, it's not like this is…there was a higher margin for error, so that kind of made it more believable."

P25: "Yeah. I had high trust that it wasn't going to go particularly over – I had trust it wasn't going to go outside those bounds, but obviously I had no idea what it was going to be within those bounds, so naturally I just took the higher number. So I didn't trust it to be in the lower bound, but I trusted that the higher bound was going to be reasonably accurate."

This behaviour did work the other way too, lowering trust in the presented data where expectations weren't met.

P1: "Yeah, I felt that for some highly populated areas along bus routes there seemed to be a lack of bus stops. I would just assume there would be more."

P24: "I'm going to say a 5 because there were a few quite big figures that I was like, why's that so different, without knowing the background or anything else, yeah."

P33: "…considering out of the twenty-five sites only four had poor accessibility, to say that the other twenty-one sites all have exactly the same accessibility, I don't believe. "

Ambiguity in data descriptors

Participants struggled significantly with the ambiguity that they saw in some of the dataset headers, or descriptions of them. Accessibility ratings of "Poor" or "Good" generated a lot of discussion on fuzziness of the header and the data itself. Nearby bus stops also stimulated the same sort of discussion, group 9 didn't agree about how to handle the route data,

P33: "Oh, I mean, five. What counts as nearby? I mean for someone that can walk, I'd say ten minutes is probably nearby, but for someone who couldn't necessarily move around very well, ten minutes is probably a very long way to get somewhere.

P36: The stop is either there or it isn't, though.

P35: It could be five minutes down the road, which, for my grandma, would take about an hour.

P36: But most buses stop right outside them. I know it's not all hospitals but—

P33: But it doesn't say that does it? It doesn't go 'nearby means it's at the door'."

Broader data trust attitudes

While capturing trust scores for each dataset, more general attitudes towards trust in this scenario also emerged. Trust scores didn't ensure or preclude dataset use in the group decision process. This included how the groups identified varying levels of data quality, the effect on the trust in that data, and how they handled it for the purpose of the task.

P23: "It's like, you know, if you've got shit data, you've got shit data, you can't do anything about it, you've just got to use it, haven't you?"

Group 8 were clear about how they were allocating trust in their task, this is also revisited in the next subsection seeing how trusting groups were had access to metadata in their tool,

P29: "10 across the board for every dataset, because we've got no idea where any of it came from and it was a task that was put in front of me. Like there was – as in, there was no context where any of it came from… there's no point in that time. Because if you give someone – what was it, forty-five minutes or an hour to do the task, forty-five. Forty-five minutes to do a task, if you start questioning the data you ain't getting the task done, you've got to roll with it. Because there's no way you're going to be able to pull a second dataset out."

Metadata

This subsection highlights influences that the abstracted and detailed metadata had on group trust of the datasets.

In the abstracted version, the most valuable metadata was in the sets that had "No Data" and erroneous values. The red text highlighted quickly to the groups where data was missing or to take care.

P8: "Also, it highlighted where there was no data.

P7: Yeah, that was helpful.

P8: Because that was red, you saw that straight away."

P32: "Of course traffic light system is more useful than not having it at all. Because otherwise we'd have trusted all of the data fully and gone, oh, we're well under budget, 375 quid instead of 375,000 or whatever it was, so obviously that bit is useful. Yeah."

This prompted the approaches presented in section 6.1.4 such as dismissing the errors and replacing with figures from sites of the same pod number or facility type.

P32: "So for example, I think it was site 24 and 25 up in the corner they were exactly the same on so many things, and then every now and then there'd be a red and it would be completely off. So I don't trust that data, but actually I do trust the data from the other site, to guess what that data would be."

Where there was abstracted data quality presented, the colour of the traffic light was tightly linked to the trust the participants placed in the dataset. The extract below is indicative of how participant 20 rated all of their data trust scores.

P20: "The majority of that is in green and some of it is in red, so I'm going to say a 7…More of that is in green so I'm going to say 8…Oh, that's weak. I'm going to say – it's all there, it's all orange, so I guess 5."

Group 8, that placed a trust score of 10 across all datasets explained the role of the traffic lights to them,

I: "Okay, so what I want to get at is what data you didn't trust.

P30: The red.

P29: The red.

I: So just simply done on colours, I can take your—

P30: I was going to say, without meaning to go all like fourth dimension on you, anything that you told us not to trust by putting it in red we therefore didn't trust. (Laughs)"

Groups did dismiss the data quality information in some cases due to the time constraints. This was more prevalent in the groups presented with detailed metadata,

P9: "Honestly, don't think I noticed it. Definitely didn't use it. There were too many numbers and my brain couldn't handle the numbers, I don't think."

P21: "I did see it. I registered it for the population data and then discarded it on the basis I didn't have time."

P23: "Noticed it was there, realised I already had too much information anyway and it's not useful and just… yeah. Ditched it."

Presenting data quality metadata, either in abstracted or detailed form, functioned as a reminder to groups that not all data was trustworthy and they shouldn't necessarily take it at face value. They took some time to judge the datasets, then continued the task with this sense of data quality.

> *P18: "I looked at it when it was orange, and I was like, why do I think it's gone orange? And then it was clear that even though the population data was orange, the numbers of like which sites were going to have – the site that had the most fifty plus had like three or four times the number of the least. I was like, that's going to be significant enough to target one over the other anyway, even if the quality's not a hundred percent. So I was like, I reckon it's mostly trustable, even if it's gone orange."*

> *P10: " I figured they were all – the ones that I checked at least, were sufficiently high for me to thin it was fine, if you know what I mean…The ones that I saw were mostly over 85 per cent…85 per cent plus is the ones that I happened to see, so I was like well, if this is the general quality of the data, or at least the completeness or the accuracy of one of them was that high, it was like right, you know, it's not like we're working on two per cent of completeness here. It's almost all there."*

Proposal Confidence

In discussing their levels of confidence in the proposal they decided on, groups emphasised the influence of time scarcity and some ways their confidence could have improved.

Time scarcity

Feelings weren't uniform on the degree of time pressure felt while completing the task. However, in terms of influencing the confidence in their decision, many participants pointed to the limited time available as reducing or limiting the confidence they had in the proposal. A few accepted the time limit as part of the scenario, capped the confidence they could have in the decision, and were happy with that.

P3: "I don't know if this is the sort of thing where you could ever have enough time because of the level of data, you could just go on and on. So given the time we had, I'm glad we came to an answer. But always would have wanted more time."

P30: "I think from my perspective probably an hour would have been the ceiling before it would have become much more like methodical and meaty. But then something like that, if you gave me a whiteboard, I could spend days doing that and have a lot of fun with it. "

The feeling of the time pressure was exaggerated by the relative quantity of data they were presented, and the use of a bespoke tool of which all participants were novice users. This meant some of the task time was used learning how to use the tool, understanding the task, and exploring what data was presented in the tool,

P17: "Yeah. It's just knowing how to get the data we need where we can see it…I wanted more. I'd say half an hour more, given that at that point we'd gained momentum. I think once we had that first shortlist we were gaining speed,"

P34: "I think we were getting to a good point by the endpoint. I think another fifteen/twenty minutes we would've got a decent answer. But I don't know whether that's because we sped up in the last five minutes.

P35: I think another fifteen minutes we would've got a solution but you could've spent a lot longer to get the optimal solution."

Desires to improve confidence

Beyond having more time, participants indicated a number of tool and task features that they'd have appreciated having to improve their confidence in the decision they made. These were mostly around the ability to forecast or model outcomes of a series of proposals, giving them ways to compare these proposals, and some additional information on some of the datasets.

P4: "I think it would have been good if we could have ran a model based on that. Like this is what it looks like based on the selection, or something like that. Then I don't know, do you know what I mean, just to give you that confidence. Or if you *could have compiled his proposal, one proposal, two proposal, three, and have put those, you know, here's what we selected for this. Okay, now let's go to proposal two and we'll reselect stuff. And then had them and then ran them in a situation or something…Yeah. And had yeah, like here's three different models with three different bases, when we run it, this is what it looks like. Then I think you could try a different approach, because it may have been that we could have tried going for a super expensive, dense approach and that actually ended up working better."*

P13: "Probably being able to do – to look at more combinations. I think we kind of picked a combination and went with it, because of the time. Rather than try adding in a couple and taking a couple out."

Desires for tool features

In discussing their experience using the tool, and describing how they used the features available, participants expressed a desire for other features in the tool that would have supported a different decision process or improved the process they had been using.

Since many groups prioritised sites using population figures, features that would help them find sites that reached the highest proportion of the elderly were focused on. Group 1 and 9 described how they'd like to see population data visualised on the map,

P4: "Yeah, I would have liked to have – ideally, I would have liked to have been able to see a heat map of population across the whole thing. So then I could have seen just distribution of population regardless of age, but also then subset, like sub divided by age, so I could see where I'm trying to target. Because otherwise I'm having to click on and off, stabbing in the dark, trying to try and guess that information. Whereas if I just had that as a heat map, that's a hundred percent accurate based on that 300K population. We can sit back immediately from minute one and say, right, here's generally speaking where the majority of our population is, this is who we need to serve."

P33: "Being able to put all the information of population density and stuff on the map would've been nice as well.

P35: Yeah, map overlays."

P4: "If you had an accurate heat map you'd be able to literally look at that and say, yes, I know for a fact that I'm going to service these people, we're within a mile radius of these people."

Participant 4's point raises an aspect that will be returned to in section 6.2 about the assumptions of the data quality for map visuals.

This was a synchronous distributed group decision task, and as a result of their approaches, groups indicated they could have been helped with ways of syncing, maintaining, and restoring their common operating picture.

P2: "Maybe something that could unify us all together, a button which is like, copy this person's current selections or something would be cool. "

P28: "So we're working as a team, right, so I really would have enjoyed a kind of a more interconnected kind of sense to it. Because I know we couldn't share screens, so it would have been really interesting if we could almost link what we were seeing at the same time, I think that would have been really helpful. "

Mostly, participants wanted greater control over the datasets that were visible and the formatting of those on the screen. Participants wanted the ability to remove and add datasets to either declutter and focus on fewer sets, or to compare site metrics more easily. This desire meant they also wanted to be able to move the displays, choosing to compare two sites side by side, or manipulate all sites by a dataset to help in their sorting and elimination process. In this same way, participants wanted help from the tool in tracking how they were doing against constraints and proposal metrics, with features to flag if they were exceeding constraints or that they'd improved the outcomes with a change to the proposal.

P21: "Maybe it needs to be a little bit flexible so that people could pick what they wanted to show. But I could see it having say four boxes at the top and one of them is like a traffic lights on how much of the vulnerable population you're going to hit. One of them is how much of your total budget have you blown. So what's the total cost of your current selected sites."

P24: "I'd like to put it in order, the sites…Because it was benefiting to the way we were doing the process of elimination, like systematically going through them."

Participant 21 got round the issue that participant 24 was facing with the tool by copying population data into an MS Excel spreadsheet to manipulate.

P21: "It worked quite well for me for what I was doing. For me, I was trying to prioritise places that had the highest over seventies population first. So all I had to do is enter a site number and a seventy plus population number and then sort, largest to smallest, which is how I could immediately rule out some of the sites as just being not enough old people."

External materials and programs

Particular tool desires were described explicitly as above, however others came from how participants chose to work outside of the browser-based tool and outside of the MS Teams call the group were working in. Examples of these are also covered in section 6.1.6. These split roughly into 3 purposes; extraction of key information, monitoring of decision processes, and calculations for site and proposal comparisons.

Most participants started the task in some way with notes to remember the roles, key role information, and task information. This was done so early in their task phase, when they couldn't effectively know what information was vital, that participants would often abandon the notes due to time pressure and realisations the group could manage the information together.

P6: "So I made notes initially on my role brief thing, just key information of the staff, which I later ignored anyway,"

P10: "I guess I started off trying to write down the information that I had and then I realised obviously there's some time variable and I'm just quicker at using Excel. I can just free-for-all it and then make it more concise at the end, and then – I found it useful knowing the amount of vaccines we had maximum available."

P26: "I took the key numbers out of my bit of data and that was it. But I put the R number down for some ungodly reason, never used that again."

Participants also tracked the sites their groups were proposing, rejecting, or had accepted.

> *P1: "I used it very briefly to write down the population coverage of sites 1 to 10, because I thought that'd be useful to note down."*

> *P33: "Just to visualise what we had said, being able to cross of a list of one to twenty-five so I knew what sites we were still looking at."*

The participants used these notes and programmes to support the decision process they were employing.

> *P3: "I started with WordPad, realised I couldn't do a table, so I copied it all across to Word document, or Libra office writer, and then started doing a table. And then I realised that I couldn't actually manipulate any of the data in the table, so then I copied it across to an Excel or Libra office calc as it's called. I did it mainly because for me, just retaining knowledge, I can talk about things, but if it's not written down for me or I'm not visualising it, I just won't retain it. It's how I learn things, it's how I retain knowledge."*

6.1.4 Main themes from thematic analysis and observations of interactions during the decision process

This section presents themes that emerged from the task phase during analysis. The task was relatively unstructured, with no direct guidance given to groups on how to complete it. Transcripts were thematically analysed, firstly in vivo coding guided by the research questions for the study and the observations made by the researcher listening to groups during the task phases. Deductive coding then generated a richer set of data extracts based around the emergent themes of the inductive process. 3 key themes were identified and 5 auxiliary themes that don't form clear subthemes, interlinking between each other. The key themes were the set of emergent task approaches, the spatial and visual reasoning, and the perception and handling of data quality. The auxiliary themes cover assumption testing as part of the process, role adoption and brief sharing, group common operating picture maintenance techniques, tool navigation learning, and time scarcity indicators.

Task approaches

All groups were quiet for the first 3-8 minutes of their task phase, reading briefs and looking individually at the tool.

After identifying the task and subtasks, groups began working towards their proposals. The decision processes were explicitly chosen or evolving across each group to varying degrees. 5 different approaches can be characterised from the participants: bottom-up building, top-down pruning, spatio-visual, subgrouping, erratic or unstructured.

Bottom-up building

Groups using this approach started with a blank proposal list and sought sites to append as they worked through the task phase. How they did this varied, group 6 started as individuals working based on their role description to find and propose sites back to the group,

> *P24: "My suggestion for this, I'm just thinking, is that we each go through from our perspectives and chose the top ten sites or something that we think, based on—"*

The approach later failed as some participants struggled to understand how to assess each site using only one dataset. Before abandoning this approach, the group tried a voting system to aggregate their proposal lists, going through each and only adopting to the group proposal if a majority of them had put the site in their top 10.

Group 2 suggested a collaborative approach to the bottom-up method, to rate each site before choosing their proposed list. This approach also failed as the group abandoned the rating method, distracted by a single dataset over sites 1-7 for around 20 minutes.

> *P6: "I have done coursework like this for GIS and we went through them and rated them on different things. So I don't know if that would be appropriate here."*

Group 3 built the first portion of their list off one data tab in the tool, identifying priority sites that might be missed by the second stage of their approach.,

> *P11: "Well, so we want to get the maximum reach within the constraints that are set…starting with where doesn't have transport links may prove to be quite useful because that gives you the stops that are going to fall through the cracks otherwise."*

Groups that proposed or took a bottom-up approach struggled with the learning curve of understanding the datasets across the sites. They spent disproportionate amounts of time on the first few sites they assessed, often starting with sites 1-4 then being rushed to assess the remainder. The main drawback for this approach was the lack of familiarity with the datasets in the tool, meaning that participants couldn't effectively assess whether a site was any good, they didn't have the context of the wider dataset to know if the population coverage or costs were reasonable for the first sites they were looking at.

Top-down pruning

The converse of the bottom-up approach was popular with more groups. This may be related to the nature of the task structure and maximising variables within constraints. These groups started with a full list of 25 candidate sites, then a series of passes throughs the tool discarding sites for different reasons until the group had a proposal within the constraints.

Group 9 is an example of starting with broad pruning strokes before refining the rejection criteria,

> *P35: "Well, I think I can discount (pause) a huge number from an accessibility point of view."*

Group 8 had the same approach at a site level later in their task phase,

> *P29: "I'm just going to remove site 2.*
>
> *P30: On what basis?*
>
> *P29: On the basis that on the transport tab it's got no parking and poor accessibility and we're after the old people."*

These groups suffered from a similar learning curve with datasets as the bottom-up approaches but to a lesser extent, normally doing a fast pass through at least half the sites seeing the range of data in each set before starting their discard process. They compared and rejected sites on single dimensions faster than bottom-up groups compared and adopted.

Spatio-visual

A variation of both the previous methods saw some groups suggest sites to discard or look at more closely using the map, splitting sites based on their geography before looking into any of the data below the map in any depth. They took a lead from visual cues and data presented on the map. The groups using this approach progressed the fastest to an initial proposal that resembled what would be their final proposed site list.

Group 3 split their region in this way and then used the site coverage visualisations to work through a number of their sites,

> *P11: "Obviously, you've got a big cluster of sites within the sort of main town area and you've got your sort of satellite towns outside that. So there's – you can always break this down into there's your city or main town bit, which could almost act as one big spot where we need to figure out what staff do what and where they go, which site's the most cost effective. Then there's outside that, which is we need to make sure that everyone that needs access has it."*

> *P11: " Something I've found out is the travel distances vary. It's not a distance, as such, as a travel time. So for example, site 9 covers a large area on the travel distance too, whereas sites 4 and 13 cover much smaller, comparatively smaller areas. So potentially finding sites that can cover a larger area. I'm just looking at what the population differences are. Yes, so the larger area, somewhat predictably, has more people in it."*

Subgrouping

In a similar way to above, many teams demonstrated a subgrouping approach, this restricted the 25-candidate site list down to a series of sub tasks, deciding between geographically close sites. The decision within these subgroupings would usually employ a compare and discard approach. Whatever grouping size was being assessed, teams wanted to reduce to a single site that would be added to their proposal list, and looked for reasons in each data tab to reject sites.

> *P5: "Yeah. I think if you just highlight, what we could do is if we compare one, two and three, that's how many sites in total? If we compare the first three in one*

go, we can have a look and then we can rank them and pick the best one out of those three"

P33: "I think we should pick between twenty-four and twenty-five, just because there's… (Overlapping speech)

P35: I've got five sites where I think we need to pick between them. "

Erratic or unstructured

Though most groups set out with a planned approach, some evolved into haphazard movement around the map and sites. Group 6 described first using bottom-up moved to erratic decision making over course of the task phase. Some sites were voted on, some rejected on single datapoints,

P22: "Then what we'll do – I think you pick your own preferences and then there's almost like a bit of a trading war at the end, where we go, well, you know, we adjust it at the end. "

Freeze

Group freeze wasn't a purposeful approach, but was a behaviour observed across a few groups. These teams tended to begin with a clear method in the way others did, but collapsed with individuals struggling to understand their role-relevant information or not knowing how to compare and select sites for their datasets. This was mostly seen with the groups that started bottom-up, their limited exposure to the extent of datasets meant they had minimal reference points other than any existing experience or preconceptions. These groups changed approach multiple times and voiced greater feelings of the increasing time pressure over the task phase, leading to essential freeze and near abandonment.

The set of observed approaches indicates the sort of behaviours and cognitive processes that could be better supported or accounted for in this sort of scenario.

Spatial/visual reasoning

Following from the task approaches adopted by groups, this subsection expands on some interactions between team members that indicated the level to which they were using visualisations on the map and reasoning spatially to adopt or reject sites. There were some explicit spatial and spatial-related references in their reasoning. These references were also heard in how the groups navigated the tool together, orienting themselves in their personal views as if they were looking at it together.

Groups 5 and 7 show some further examples of the spatial approach described in the last subsection,

> *P25: "So it looks like we probably want to treat the – basically the west side of the map – the north side being both Bromfol – both West and East Bromfol and the east side of the map being pretty much everything else, maybe as three separate zones".*

> *P19: " I think it would be beneficial. Because if you had site 1 to 4 that would include bus route 4 which covers East Iverswood, West Iverswood and – basically that big gap in the middle."*

> *P26: " Well, 7 starts going into Cleverhill, if we move 8 and 7 and go 6 instead that sort of makes it more rounded. Or shall we go 8 and 6."*

Group 2 took a combination of spacing on the map and the bus route overlay offered in the tool,

> *P2: "No, I'm just wondering then do you include the northern ones then as 18 and 17? Because at what point, how are you dividing it is more my point?*

> *P3: The reason I don't include 18 and 17 is because they're on a public transport route that connects."*

The site icons were also employed by some participants in their decision process, making their parsing of the sites faster while also helping to orient their team members with the same site they were discussing,

> *P3: "Existing health infrastructure is probably going to be the best then for—*

> *P4: Yeah, the heart places seem to be good, solid – seem to cover a good area of people."*

> *P7: "Seven, eleven and fourteen, yeah, that's—*

P6: It's that spatial thing, yeah? So we've got three—

P8: Also, seven is already— It's the love hearts in bold, so that's already a—

P6: A health centre."

P17: "Have you guys seen, if you open the cost tab and then go back to the map, there's little pound symbols on each sites, so we can get a quick look at how much it'll cost to put things in each place. "

This subsection and the visual approach to decision making will be returned to in the discussion in section 6.2. It's important to understand how much groups do this without any instruction to do so, in the context of data quality and data trust.

Perception and handling of data quality

In addition to the focus groups understanding the extent to which groups considered the quality of the data presented in the tool, the observations of interactions in the task phase showed how differently some of the groups handled this. Not all groups appeared to notice some of the manipulated data in the vaccine throughput figures, staffing requirements, and site preparation costs. Those that did either discarded the site on the basis of that data, ignored the lack of or potentially erroneous data, or looked for ways to estimate another figure to use in their decision process.

The "No Data" instances in the vaccine throughput dataset were most readily spotted, as text in a column of numbers they stood out. Though some groups didn't realise until late into their task phase and couldn't do much to mitigate against the finding.

P2: "Yeah, so operation, site 1, we're doing model 1, and so we need – let's call it 687. Site 2 is the same number again. There is no data. Shit! So I guess we need to look at who's actually—"

P30: " On what basis have you made said decision?

P29: Lack of good quality data on throughput."

Others found ways to handle the missing values, *P10: "Yes, but on the operational side – so 18 you said.*

P9: Yes.

P10: There is no data for the amount of people it can handle per day. That's not helpful.

…

P11: But if we look at a similar model, so if you compare it to 17, you've got the same number of staff. You've got the same number of pods. It appears to be pretty much identical. In fact, it appears to be exactly identical… So I'd say it's worth risking the fact you don't have any data on throughput based on the fact you've got the same number of pods, same number of staff and the same number of potential volunteers. "

Participants without the abstracted metadata did raise some questions around data quality when figures seemed outside their expected ranges, but this wasn't as consistent as those with the traffic light system flagging the missing or erroneous values. Group 2 and 5 had access to the abstracted version of the tool,

P6: "Twelve needs a lot of staff.

P8: Okay.

P6: Well, that's what it says, 'Staff needed', but then it says— That's in red, so that's low data quality, but it says 2,500 staff needed.

P7: Yeah, that's a lot. Also, yeah, number of pods, one. For that many staff for one—"

P17: "So site 22, the thing with these community centres, they can give out a lot of vaccines but the cost of preparation is 5,000 for Biomax – it says 220 for Phastech but that's low quality data, but compared to the existing infrastructure which is 0, then there's a cost there. "

Whereas group 7 had no metadata available in their tool, *P28: "No, so – you can – hold on. Cost of operational... interesting. So 24 is a lot cheaper to set up. To the point that I almost think he might have made a typo on site 24. Because site preparation for both on 24 is £375 which seems very wrong.*

P26: It's in the data, we're using that number, that's much better, that'll save us money."

This excerpt presents an example of a group without metadata noticing the bad data, but not doing anything to discard the figure or site, using that number in their decision. In this instance the choice to use the erroneous data could cost them £375,000 in the outcome calculations. Group 7 didn't end up using the site due to a decision later in their task phase using other datasets, but throughout they were prepared and happy to use that figure and site.

Group 9, with access to the detailed metadata, had a similar interaction,

P33: "Four is the best numbers-wise.

P35: Yeah.

P36: Four? Four is the cheapest to run.

P35: Let's go with that, given we've only got seven minutes."

They were going to miss an erroneous figure for the set up costs of site 4 that would send them over the budget and cost them significantly. In a similar way to group 7 they didn't choose the site in the end. They readily accepted the erroneous cost data in site 4 set up, and also accepted erroneous staffing data but used that to discard the site. In this case the staffing was listed as 500 required to staff a pharmacy site, all other sites of this facility type took 50 people. The group didn't question the figure, incorrectly justifying the requirement as appropriate for an existing healthcare infrastructure in a large hospital near the city centre.

Groups 6 (detailed metadata) and 7 (no metadata) showed how participants handled uncertainty in data that were presented in ranges. This aligns with their described behaviour from the focus group questions on data trust,

P23: "Right, what does that put us at cost wise?

P24: I'm just adding them up, and I'm going for worst case scenario because I don't really know how to use these ranges."

P28: "Consider, honestly, when it gives you a range I would estimate the upper end.

P26: Yes, which just means you can operate.

P28: There's no way anything ever comes in under budget."

Assumption testing

In their use of the tool and process of understanding the datasets they were presented with, several participants proposed assumptions to their group, then sought to validate them.

P10: "Would I be correct in guessing that existing health infrastructure have the cheapest ones, then it's pharmacies, then community centre, then sports facility in terms of set up cost?"

P30: "Is there going to be a difference between them?

P32: There is—

P30: We've got no data on vaccines per day for site 24. But all of the other information is exactly the same. So one could presume with the same number of pods, same staff needed, same minimum medical staff, same maximum volunteers, that the number of vaccines per day would also be the same. What happened?"

P30: "Yeah, but if we clicked on all of the 25 sites that wouldn't tell us the total, would it? Would it? I'm going to try that. You guys carry on without me, I'm going to see if that gives us a total. There must be overlap, it can't be that easy."

Role adoption and brief sharing

Participants readily adopted the roles they were given. Beyond introducing themselves and their role-specific data they engaged well with the sense of having a domain to be responsible for in creating a group proposal. All groups started with an exchange of role titles and role data,

P4: "So I'm FD, what are you guys, role wise?

P3: I am the transport role.

…

P1: I am the head of public health role.

P4: … we've got a financial budget of 4 milli to work towards.

P1: I have information about the case rate, hospitalisation rate and death rate between age groups as well. And the current data on the cases, hospitalisations and deaths in the area. …

P3: And in the transport role I have a detailed capacity of the public transport in the area. I have details of what roads are closed, I have details on the bus routes, where they service and their capacity. And I also have information on the percentage respondents likely to use for journeys similar to that length."

These are the sort of exchanges that lead the notetaking that's covered in other parts of this section, capturing role titles and key information to take into the task.

The roles influenced some of their task approaches, with groups trying to divide up the data between the relevant roles to reduce the workload.

P35: "So does one person want to look at accessibility, one person at population, one person at cost, and one person at the operation? Does that make sense?

P36: Yeah.

P35: Rather than us all looking at the same thing.

P36: Do you want to do it by what everyone's job is, just as the easiest thing?

P35: Yes."

Group COP maintenance

Initial role sharing and brief sharing initiated the groups' common operating pictures, knowing who had what perspective, and the situation they were dealing with. Throughout the task phase, groups maintained their picture with recurring behaviours, notably tracking of sites each had selected or the current proposed site list they were working with,

> *P4: "I've got quite a decent spread here, covers up to 400,000 people, which obviously is a lot of overlap. But 37,000 in the seventy plus range and the cost is – on model two is in budget 3.7 mill and model 1 is 3.7 to 4.3, so it's sort of right on the cusp. And it's got a good spread across the whole map. Maybe put this forward as an initial proposition, if someone – [Participant 3], are you taking notes, do you want me to just…*
>
> *P3: Yeah.*
>
> *P4: …fire those off. So we've got site 1, 5, 6, 7, 9—*
>
> *P3: So 1, 5, 6, 7, 9.*
>
> *P4: 13, 14, 15, 18, 20, 22, and 23."*
>
> *P25: "That's fine, we won't do that then, that's no worries. So what I will do is – I'm just going to arbitrarily shout out these sites for people to select, just so we're all looking at the same sort of overall map. So deselect everything. So we'll start out going from west to east, so say site 25 in the north, site 23 in Salkin, site 22 by South Kemppat, let's say 17 in West Bromfol, site 15 in East Bromfol, site 8 in Bridtowatt, if you can all see that? Yes. Then in East Iverswood we'll say site 11. Site 14 in West Iverswood. Site 10 and site 3."*
>
> *"P30: Right, you got rid of 14 and I did not. 4 and 6 have gone. [Participant 29], can you just – for my sake and perhaps for the benefit of the other lads, can you do a roll call of the ones you still have left in?*
>
> *P29: 1, 3, 5, 7, 9, 13, 15, 20, 21, 22, 25."*

Tool learning and navigation

As the participants learned more about the tool they would often share features or points of interest with their group. In the same way, as described earlier in the way groups handled the distributed nature of the task, the participants called out features to help navigate the tool together as if they had a shared view, an extension of the COP maintenance.

> *P3: "Okay, I've got a thing that you should all do right now, I think it's quite useful. If you look at the transport tab and if you click at the bottom, show routes. This is a useful thing to consider."*
>
> *P22: "I don't know what these pods are, what's a pod?*
>
> *P21: No, I don't know what pods are.*
>
> *P22: Number of pods, total model, model – what's model? What's the model? Model 1, model 2, no idea.*
>
> *P21: If you click on – so if you click on it, it gives you a little popup. So if you float it over, if it goes a funny – if it goes grey when you float over it, then you can get it to pop something up and it'll tell you."*
>
> *P24: "Does anybody know what the item of service fee is?*
>
> *P21: I think it's in the cost tab. Does it not have a little thing that you can float over and it'll tell you?*
>
> *P24: It's in the floaty thing.*
>
> *P21: Which one did you click on to get it?"*

Time scarcity indicators

Time scarcity is explored in the reported experiences from the focus groups in section 6.1.3, this subsection highlights some of the repeated utterances during the task phase that indicated how participants were feeling the time pressure. The pressure was mostly imposed as a function of the information and time available,

> *P2: "But it's just too much data for forty-five minutes (laughs). "*

> *P23: "It's too much information to handle (laughs)."*
>
> *P35: "Sorry, site five. Site five.*
>
> *P36: Oh, we've got five minutes.*
>
> *P33: Stress. Oh my God, I feel like I'm in an exam (laughs)."*

This time pressure influences most groups more as they approached the deadline to form their proposal,

> *P29: "The cost of which is looking expensive. How much did you say we need to cut, mate?*
>
> *P30: 20 grand. We don't know the – there's a big red mark on the cost of site 13, cost of preparation.*
>
> *P29: Yeah, delete that, we're running low on time."*

6.1.5 Summary statistics of the tool interaction captured by the interface

Tool logs captured the click interactions for each button throughout the task phase for each participant. From these clicks a series of interaction profiles could be calculated. The tool was built with 5 main dataset groupings, with 5 data tabs and therefore 5 buttons associated with each data grouping. These 5 were a tab for: briefs (study and role), costs (preparation and operation), operation (vaccine throughputs and staffing needs), population (site catchments for age bands and travel distances), and transport (parking, buses, and accessibility). One of these was always in focus on the tool once the task started. All other buttons were associated with the site selection/deselection, additional visuals within data tabs, and dataset headers.

Table 6.10 shows the average times each data tab was in focus for each group, and the average focus times for each of the metadata abstraction levels. The next table allows for easier comparison between groups and metadata versions of the tool.

Group		Brief Average	Cost Average	Operation Average	Population Average	Transport Average	Total Average
Non Meta	1	00:08:41	00:04:49	00:11:36	00:15:14	00:04:13	00:44:34
	4	00:07:16	00:05:06	00:17:34	00:09:52	00:03:59	00:43:47
	7	00:07:03	00:11:11	00:03:53	00:15:12	00:03:42	00:41:00
	Average	00:07:40	00:07:02	00:11:01	00:13:26	00:03:58	00:43:07
Abstract Meta	2	00:09:01	00:15:47	00:12:21	00:16:30	00:02:41	00:56:21
	5	00:10:14	00:05:29	00:11:08	00:13:11	00:04:45	00:44:46
	8	00:09:51	00:12:37	00:06:36	00:09:55	00:05:49	00:44:47
	Average	00:09:42	00:11:18	00:10:02	00:13:12	00:04:25	00:48:38
Detail Meta	3	00:12:33	00:10:56	00:07:45	00:19:37	00:02:58	00:53:49
	6	00:08:30	00:10:42	00:06:55	00:15:22	00:02:54	00:44:23
	9	00:07:10	00:11:19	00:10:08	00:11:21	00:07:34	00:47:32
	Average	00:09:24	00:10:59	00:08:16	00:15:27	00:04:29	00:48:35

Table 6.10 Tool Focus Times Split By Data Groupings And Tool Version

Table 6.11 converts the focus times for each group and data tab into a percentage of the total task times. Now it is apparent that groups spent roughly the same proportion of their time on the briefs tab. This was concentrated but not limited to just the early task phase period. Across all groups there were participants that clicked back to the briefs tab and checked/confirmed both main brief information and role specific data. Similarly, the groups spent the same proportion of their time on the transport tab, this was the lowest focus time tab for all groups and metadata versions. Though differing by a little more than the proportion on briefs and transport, the most time as a proportion of their task for all metadata abstractions was spent on population. This was on average, in this there is more variation between groups within tool versions, either the order of focus proportions or in the differences in proportions. Group 4 stands out as a much lower percentage of their time spent on the population tab, and significantly more on operations. Group 8 and group 9 deviated from the others in their metadata version. Over the 3 remaining data tabs, the groups differed their proportion of time spent on each.

Focus changes were also calculated with the focus times for each group. This was the number of distinct data group tab clicks for each group, how frequently the members were toggling between the tabs, independent of the proportions of time spent on each. The top 3 focus change scores were spread across groups 1, 2, and 3, so one from each metadata version of the tool. Focus change frequency was roughly steady across tool versions and groups within, with the exception of group 6 having significantly lower focus changes than all other groups, which distorts the average for the detailed metadata groups. A suggestion for the reason behind this is discussed in section 6.2.

Group		Brief % Avg	Cost % Avg	Ops % Avg	Pop % Avg	Tran % Avg	Focus Changes Avg
Non Meta	1	20%	11%	25%	34%	10%	121.75
	4	17%	12%	39%	23%	9%	97
	7	17%	27%	10%	37%	9%	94.75
	Average	18%	17%	25%	31%	9%	104.50
Abstract Meta	2	15%	28%	22%	30%	5%	104
	5	23%	12%	25%	30%	11%	91
	8	22%	28%	15%	22%	13%	95.5
	Average	20%	23%	21%	27%	9%	96.83
Detail Meta	3	23%	21%	14%	36%	5%	107.75
	6	20%	22%	19%	33%	6%	52.5
	9	15%	23%	23%	24%	15%	89.5
	Average	19%	22%	18%	31%	9%	83.25

Table 6.11 Tool Focus Times As Proportions Of Total Time Spent On Interface Split By Tool Version

The process for the previous two tables was also carried out with respect to the team roles assigned to participants, as well as the groups. Table 6.12 shows the average times for each of the 4 roles on each of the data grouping tabs.

Role	Brief Average	Cost Average	Operation Average	Population Average	Transport Average	Total Average
Health	00:09:40	00:06:21	00:07:38	00:19:54	00:05:14	00:48:47
Logistics	00:10:10	00:05:51	00:15:44	00:12:05	00:02:31	00:46:20
Transport	00:08:41	00:07:20	00:07:35	00:14:01	00:06:33	00:44:10
Finance	00:05:45	00:21:45	00:07:49	00:10:49	00:02:02	00:48:11

Table 6.12 Tool Focus Times Split By Data Groupings And Participant Task Role

Table 6.13 shows these converted to percentages of total times for each role, as with the groups previously. Though not surprising, the table shows how participants engaged with the roles they were randomly assigned for the task. Roles showed the greatest proportion of their time with their respective data grouping in focus. Finance Officials spent more than double the proportion of time in the costs tab than any other role. The same pattern, to different extents, are seen for the Logistics Official and operation tab, Health Official and population tab, and Transport Official and the transport tab. Of note is the proportion of time spent in the briefs tab, with 3 of the roles sharing roughly the same proportions of focus, while those in the finance roles nearly halve the time. This is likely explained by the significantly shorter role-specific brief presented to Finance Officials when compared to the other 3, both in terms of text to read and additional data offered. This same relationship is seen in the focus change averages across the roles. This too is likely due to the shorter briefs, requiring less frequent checking, and the significant proportion of time spent on the cost datasets tab, which would reduce the occasions of focus switching.

Role	Brief Average	Cost Average	Operation Average	Population Average	Transport Average	Focus Changes Avg
Health	20%	13%	16%	41%	11%	97.1
Logistics	22%	12%	36%	25%	5%	103.9
Transport	20%	17%	17%	32%	15%	101.7
Finance	12%	45%	16%	23%	4%	74.3
Average	18%	22%	21%	30%	9%	94.2

Table 6.13 Tool Focus Times As Proportions Of Total Time Spent On Interface Split By Participant Task Role

In addition to tab focus time, overall click interactions with all the buttons on the tool were recorded and aggregated. These interaction levels were grouped by metadata abstractions and team roles. The summary of this is shown in table 6.14. Participant 16 in group 4 disconnected and reconnected to the tool partway through their task, resetting their click logs, and for this reason was excluded from summary statistics. Non metadata groups were the most active on the tool, then detailed metadata groups, and the lowest rates of interaction were seen in the abstracted metadata groups. Participants in the abstracted metadata groups were the most similar in the extent of their interaction with the tool, with the 3 lowest ranges (maximum clicks in a group to minimum) all within that abstraction level. Detailed metadata groups showed the greatest differences in interaction within groups.

Interactions across roles reflected similar patterns to the tab focus times. Finance role participants were the least active with the tool on average, and the most in agreement on click levels across the tool versions. The other roles were closer in their interaction levels on average but showed greater levels of variation within the role between groups.

Group		Role				Measure				
		Health	Logistics	Transport	Finance	Total	Average	Max	Min	Range
Non Meta	1	395	256	275	292	1218	305	395	256	139
	4	262	198	372	60*	832	277	372	198	174
	7	156	366	258	240	1020	255	366	156	210
	Average	271	273	302	266	1023	279	378	203	174
Abstract Meta	2	172	229	131	104	636	159	229	104	125
	5	248	191	134	202	775	194	248	134	114
	8	278	292	172	170	912	228	292	170	122
	Average	233	237	146	159	774	194	256	136	120
Detail Meta	3	166	415	226	255	1062	266	415	166	249
	6	106	155	338	100	699	175	338	100	238
	9	163	188	440	123	914	229	440	123	317
	Average	145	253	335	159	892	223	398	130	268
Total		1946	2290	2346	1486					
Average		216	254	261	186					
Max		395	415	440	292					
Min		106	155	131	100					
Range		289	260	309	192					

Table 6.14 Click Interaction Counts For Tool Button Split By Role, Group, And Tool Version

The top and bottom 5 buttons interacted with are shown in table 6.15. As expected the most frequent interactions were with the tabs for each of the 5 data groupings. The travel distance toggle buttons in the population tab were the next two most popular buttons. The 5 lowest were all headers from certain datasets presented in the tool.

		Non Meta			Abstract Meta			Detail Meta				
		1	4	7	2	5	8	3	6	9	Total	Average
Top 5	Population Tab Counter	135	70	109	117	89	92	137	50	91	890	99
	Operation Tab Counter	106	84	76	99	86	77	115	35	96	774	86
	Cost Tab Counter	100	53	91	106	74	97	92	36	59	708	79
	Briefs Tab Counter	87	41	50	44	55	54	50	49	52	482	54
	Transport Tab Counter	59	43	53	50	60	62	37	40	60	464	52
Bottom 5	Bus Route Header Counter	1	0	0	0	0	0	0	0	1	2	0.2
	Total Max Vol 1 Header Counter	1	0	0	0	0	0	0	1	0	2	0.2
	Total Staff Mod 2 Header Counter	0	0	0	0	1	1	0	0	0	2	0.2
	Accessibility Header Counter	1	0	0	0	0	0	0	0	0	1	0.1
	Total Max Vol 2 Header Counter	0	0	0	0	1	0	0	0	0	1	0.1

Table 6.15 Summary Of Top 5 And Bottom 5 Interacted Tool Buttons Split By Group And Tool Version

The study brief button was used significantly less than the role brief button within the briefs tab, an average of 11 times per group against 28 times per group. Dataset headers made up the bottom 20 of the 56 buttons on the interface. The most used of them being site operation model 1 and 2, and the vaccine throughput headers. Header use across metadata tool version was fairly consistent, with non metadata, abstract metadata, and detailed metadata having 52, 59, and 54 interactions respectively with their headers. No groups showed a significantly greater inclination to seek additional information from that presented in their briefs, in the main data tables, and on the map.

The site popularity for proposals in section 6.1.1 are combined with the site interaction ranks and presented in figure 6.5. This scatter plot of the rank of site button interactions against rank of site selection popularity in proposals has a correlation coefficient of 0.423 and shows a weak positive correlation between the two ranks. This is discussed further in section 6.2, it is suggested that groups spent similar amounts of time interacting with sites that weren't included in their final proposals as part of their decision process of eliminating and accepting sites.

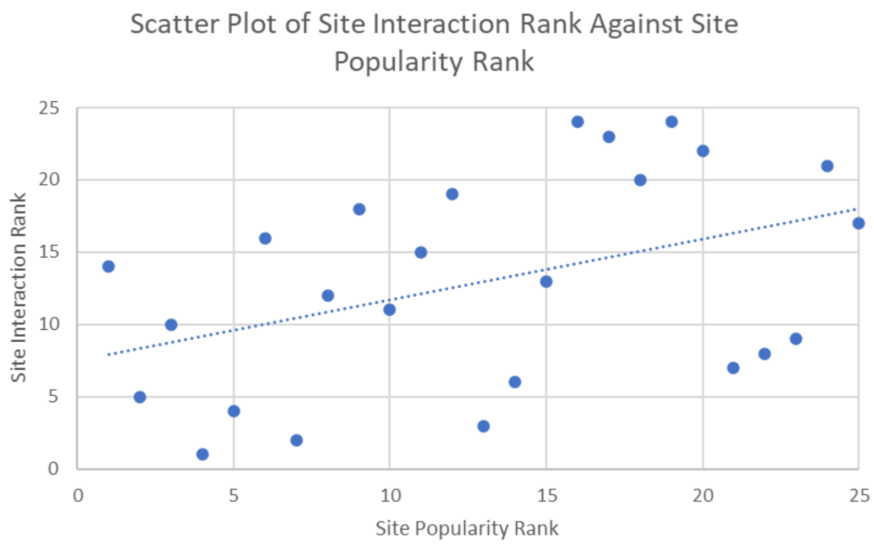


Figure 6.5 Plot Of Site Button Interaction Levels Against Popularity In Group Proposals

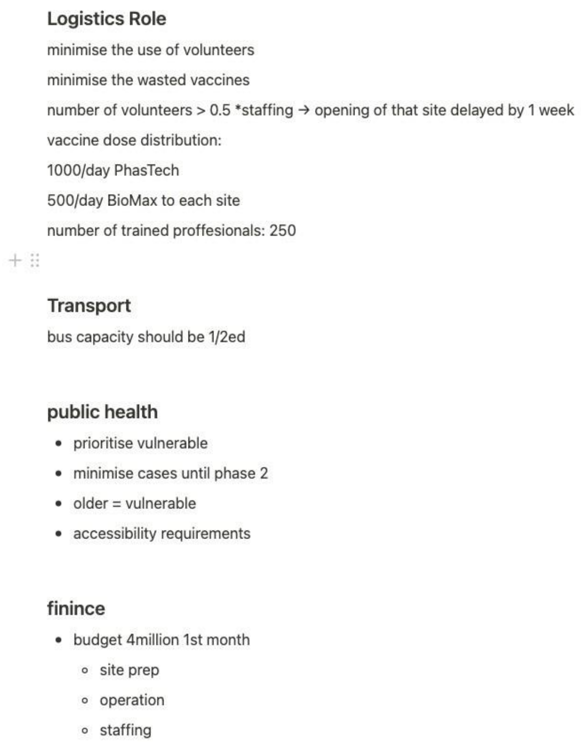
Full tables of these interface clicks are included in appendix G.

6.1.6 Artefacts of the decision process

Artefacts from each participant were collected at the end of the focus groups, these were materials from any working outside of the browser-based tool or MS Teams this included: word processor documents, MS Excel files, notepad text files, and handwritten notes. Some key features and recurring themes were identified and are presented in some samples in this subsection.

Many participants adopted notetaking in some format early in the brief reading and task phase to list what they perceived as key information from the main study brief, their role brief, and their team members' role briefs.

The structured notes from participant 34 in figure 6.6 show this process. Participant 34 was the Logistic Official for their team, noting mostly information from their role brief, then capturing at least one key point from the rest of their team members' briefs that were shared verbally.


Logistics Role
minimise the use of volunteers
minimise the wasted vaccines
number of volunteers > 0.5 *staffing → opening of that site delayed by 1 week
vaccine dose distribution:
1000/day PhasTech
500/day BioMax to each site
number of trained proffesionals: 250

Transport
bus capacity should be 1/2ed

public health
- prioritise vulnerable
- minimise cases until phase 2
- older = vulnerable
- accessibility requirements

finince
- budget 4million 1st month
  - site prep
  - operation
  - staffing

Figure 6.6 Note Excerpt From Participant 34

Participant 29 did this by lifting their key information from the brief into a word processor with a screenshot of the table of data they were presented in their brief too. Figure 6.7 shows the blend of typed, copied, and screenshot information that the participant chose to focus on.

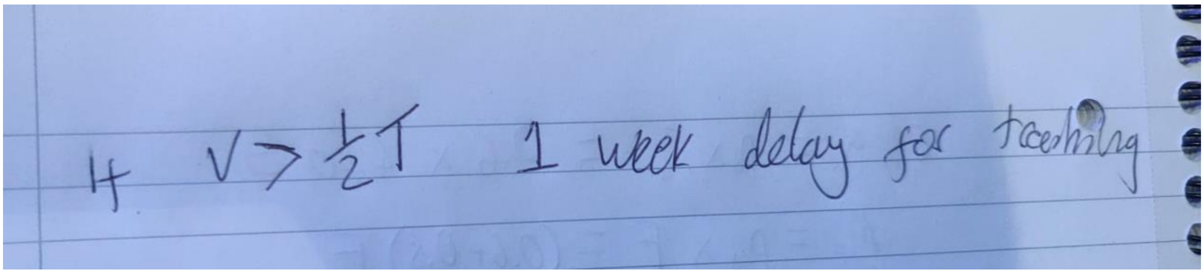


Figure 6.7 Note Excerpts From Participant 29

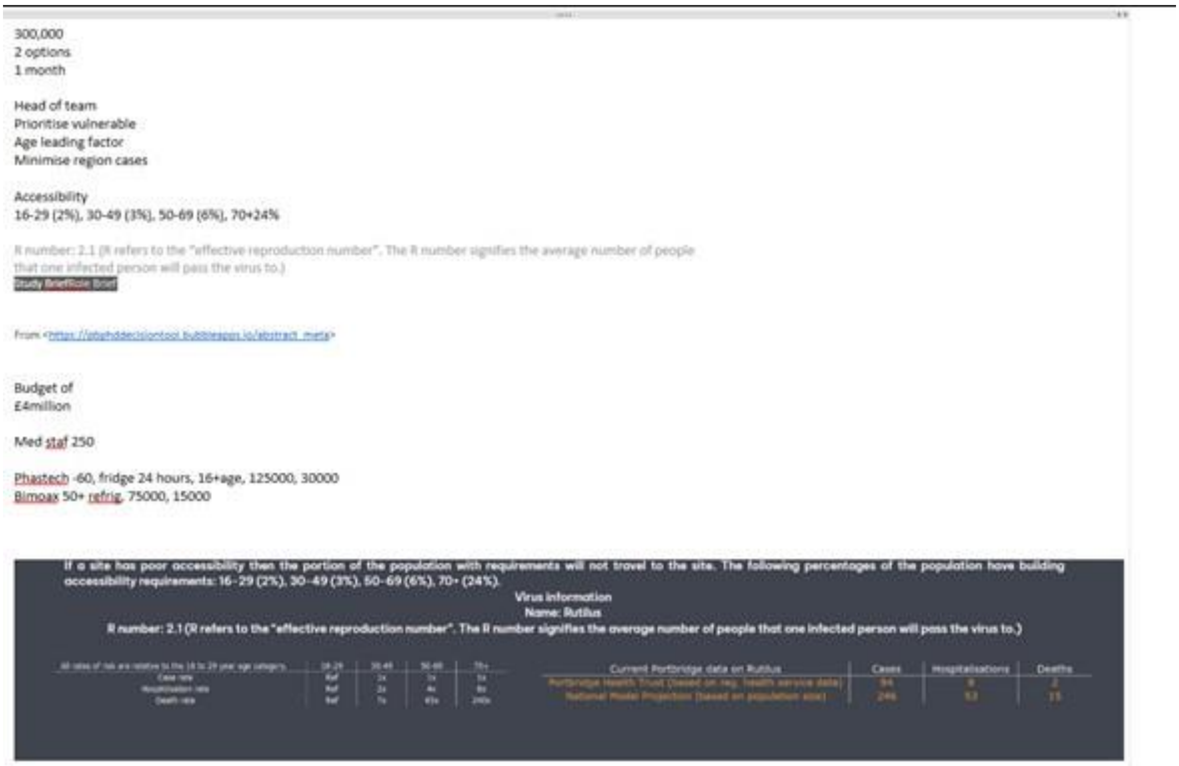


Figure 6.8 Note Excerpt From Participant 2

Participant 2 in figure 6.8 simply listed the relationship between volunteers and medically trained staff that would trigger site delays for training.

This notetaking behaviour wasn't maintained throughout the task phase, or by all group members. Figures 6.9 and 6.10 are two examples of abandoned notes. Participant listed some candidate sites once, then stopped taking any physical notes for the remainder of the task. Participant 19 extracted key study brief information for the overall task, listed the roles and the associated team member, and then abandoned listing all key information after the Logistics Official was done.

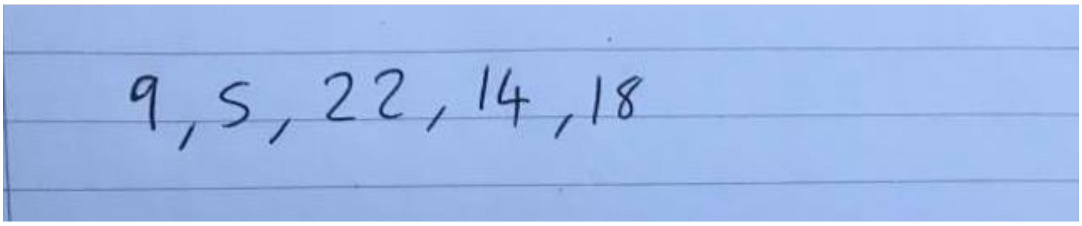


Figure 6.9 Note Excerpt From Participant 12

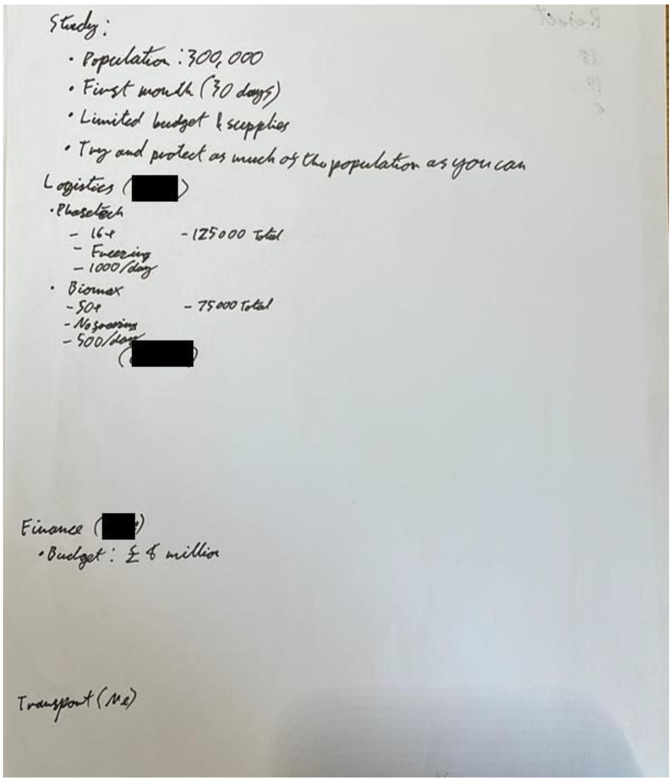


Figure 6.10 Note Excerpt From Participant 19

Participant 12 listed some and 19 abandoned their notes.

Some of the decision processes emerged in the notes taken by participants. In figure 6.11, participant 23 used a piece of paper to record how their group was splitting the map into settlement areas and the sites within those areas for smaller decisions on the path to their final proposed list of sites.

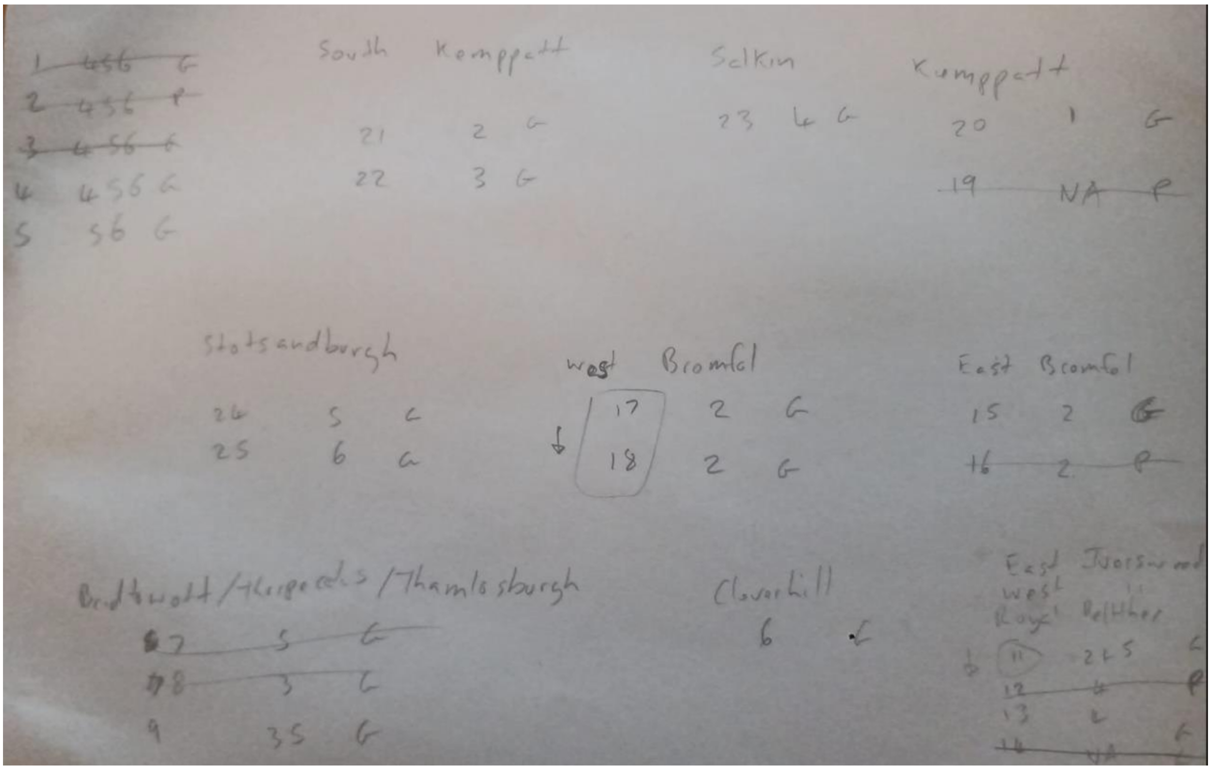


Figure 6.11 Note Excerpt From Participant 23

Participant 33 in figure 6.12 split their page in two ways. They recorded some sites that were being rejected by the group and why, these were transport-based decisions. After this initial set of 4 sites were rejected, they listed all the site numbers and visually tracked the rejections and adoptions they were making as a group.

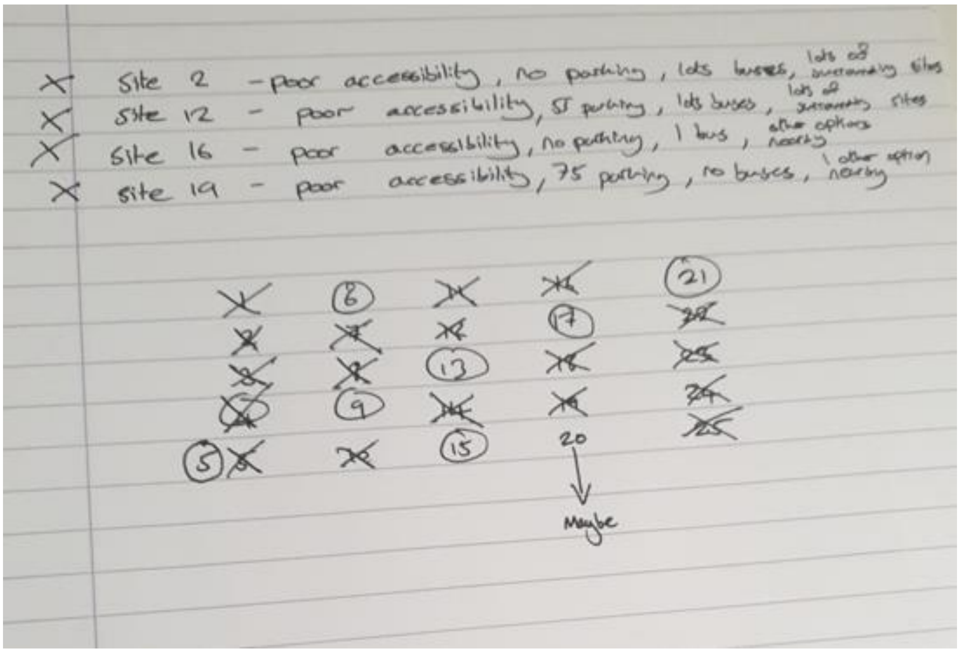


Figure 6.12 Note Excerpt From Participant 33

In a similar way, participant 35 in figure 6.13 listed the sites, briefly recording those that the group rejected from consideration and a reason why, and also noted some sites that were up for consideration, "potential". This is another example of abandonment of the external notetaking for a participant as the list is incomplete. The participant also noted the decision process the group adopted, in grouping pairs and trios of sites that were located near each other, another example of sub-decisions groups formed as a means of reaching a final proposal list.

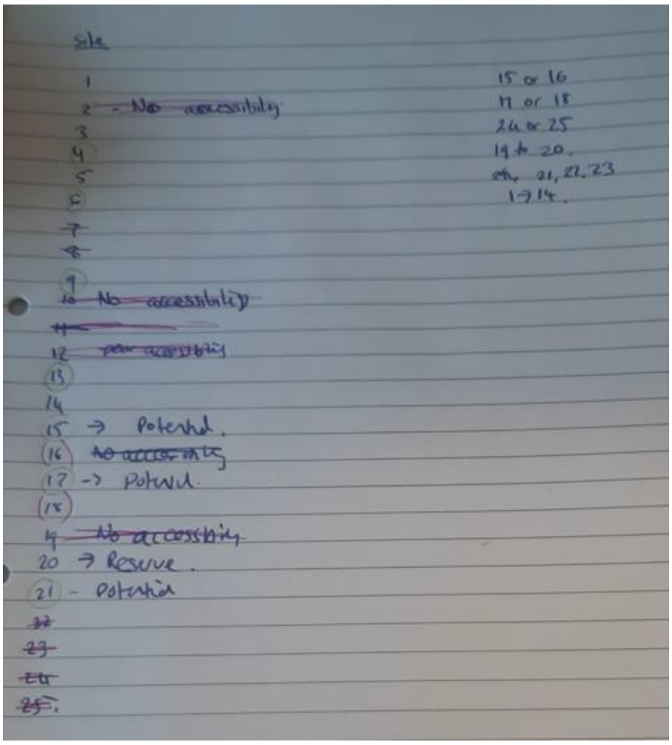


Figure 6.13 Note Excerpt From Participant 35

Participants 2 and 28 in figure 6.14 below show how some participants went outside of the tool and into programmes such as MS Excel and Calculator to assist their decision process. At least half the groups had a member use Excel at some point during the task, though to varying degrees of success whether that was computing resource splits when writing down their proposal or lifting relevant tool data into a manipulable format. Groups that copied data across from the tool commonly used it to sort sites by a dimension, here participant 2 sorted all the sites by the population reached by the sites that were in the 70+ demographic. Participant 28 used their PC calculator to compare costs of sites and proposals, summing the preparation and operation costs that were displayed in the tool as two separate columns.

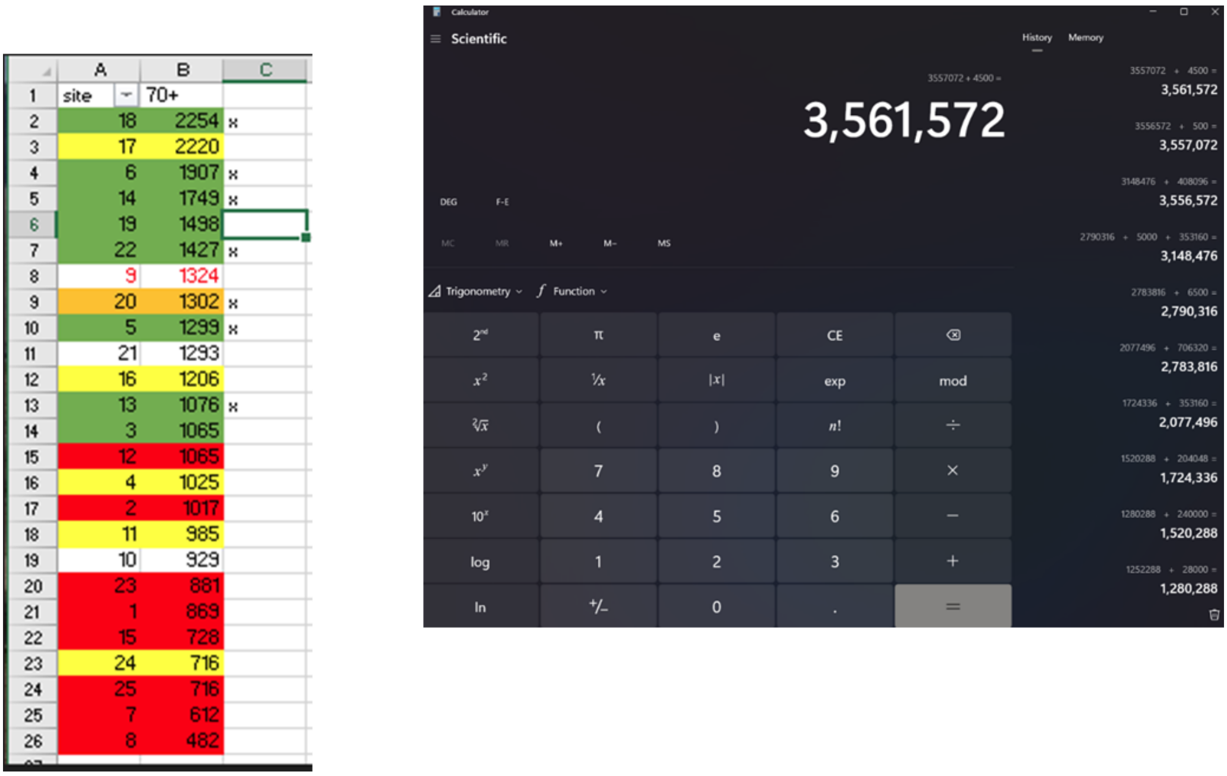


Figure 6.14 Note Excerpt From Participants 2 (Left) And 28 (Right)

6.2 Discussion

This section now discusses in a wider context the results presented, integrating the findings of the study, and returning to some of the related work explored earlier in this thesis.

6.2.1 Abstraction of data quality metadata improves data trust of non-experts while mitigating negative effects of presenting unabstracted metadata in time pressured scenario

What these results have shown is that abstracted metadata engendered greater trust from non-experts in the task data than the other versions of the tool. Taking the non-meta data groups as a control, the presentation of abstracted metadata data, with traffic light data quality indicators, increased the average trust score for all datasets except for accessibility, which was scored the same. Meanwhile, the introduction of detailed metadata in the form of source, completeness, and accuracy, decreased the trust score for all datasets except the operation costs and the car parking figures. Overall, data in the tool was trusted most by the abstracted metadata groups, 2nd by non-metadata groups, and least by the detailed metadata groups. Figure 6.15 best demonstrates this.

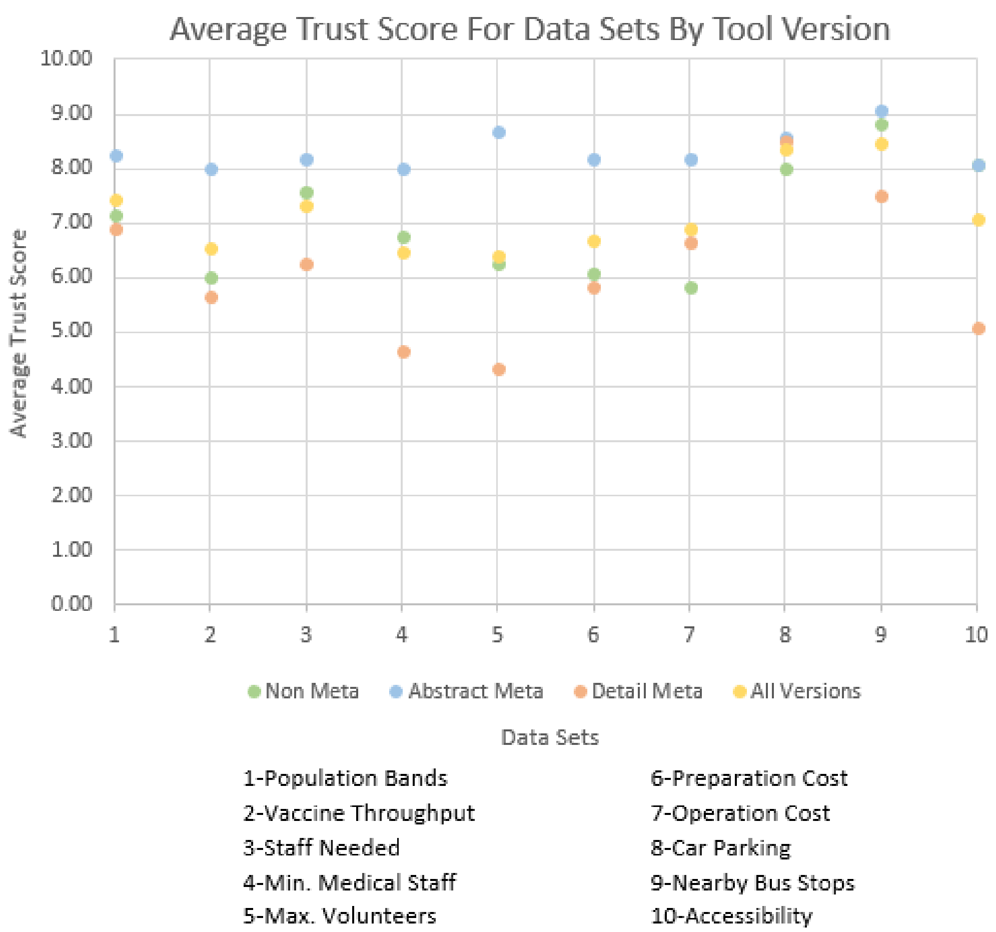


Figure 6.15 Plot Of Average Trust Scores For Datasets Split By Metadata Abstraction

In this medium time-scarce scenario, the introduction of detailed metadata negatively impacted the decision making of groups. The outcomes of their proposals were on average significantly lower than those of the other two tool versions, and they demonstrated the greatest degree of task freeze and slowest task speed. Problem structuring and decision making are affected by known cognitive biases, and time pressures and data overload compete with an individual's ability to follow effective "methods for generating, managing, and evaluating hypotheses" (Pirolli and Card, 2005). The detailed metadata groups evidenced this in the information overload exerted on them and their subsequent experience of time pressure negatively effecting the task approaches they tried. Though the groups were guided to approximately the same task times to produce their proposals, those with the detailed metadata considered and selected fewer sites that the other groups in that time period. Discussed in more detail later in this chapter, these groups performed worse that those that were provided no metadata or the abstracted version, their proposals generated the lowest vaccination levels. Weick et al. (2005) state, "When information is distributed among numerous parties, each with a different impression of what is happening, the cost of reconciling these disparate views is high, so discrepancies and ambiguities in outlook persist". Data quality metadata should have supported groups of non-experts in filtering the information space. Detailed metadata added to the time cost of reconciling the individual views, it was a further dataset that would take significant time to interpret. The abstraction was accessible by the group, helping them converge more quickly than the detailed groups, reconciling views without time cost.

High information loads can have negative impacts such as mistakes in judgement (Klapp, 1986), individuals constrained in their ability to assimilate information, filtering in an unknown information space risks loss of crucial information, leading to an overload with paralysing effects for decision makers in a time pressured situation (Lamb, 1991). Information overload for detailed metadata groups came from a quantity of information available to the groups exceeding either their cognitive capacity or the time the had available to process the information (Speier-Pero, 2019). Padilla et al. (2018) offer a cognitive perspective of decision making using visualisations. The visual encoding directs the user attention to this information that is determined as critical, a benefit to groups in time scarce scenarios.

The divergence in effect on trust in the provisions of metadata may be due to the non-expert nature of the participants, as well as a function of the time pressure. The participants recruited may not understand how to apply or interpret measures of data completeness or accuracy, and importantly how to incorporate this into decision making using those datasets. This is expected to hold true across time pressures. The time pressure in this scenario, influenced somewhat by the volume of information presented to the participants, would then serve to aggravate that inability to interpret the data quality metadata. Unable to apply this additional information, rather than providing a tool to filter the data more effectively for their decision, it would further add to the participants' experiences of information volume and time pressure. This was evidenced in the occurrences for groups 3, 6, and 9 complaining during their task phases about the quantity of information being too much to handle in the time given. They exhibited greater frustration at the volume of information than the groups from the other tool versions. To further challenge these groups, the metadata was in the pop-up headers for the relevant datasets, and so added a tool interaction for participants to reveal the quality indicators. This is also discussed later, but observations in the task phases suggest that placing the detailed metadata in the main tool display along with the rest of the data wouldn't improve the experience of participants or their usage of the metadata. This presentation would likely worsen the experience of information overload, and push participants to ignore and discard greater volumes of data in their decision process.

On the other hand, the abstracted metadata provided readily understood data quality indicators. For non-experts, the participants were likely familiar with traffic light rating systems deployed elsewhere such as on food nutrition labels in the UK. Though that instance doesn't use the indicator to highlight data quality, it does introduce participants to thresholding of values and practices of choosing between options using coloured indicators. The familiarity with this sort of indicator meant participants could readily understand and incorporate the data quality rating into their decision process. This was seen easily in the rejection of sites from proposal lists by some groups based on the presence of red or low quality marked data in that site information.

The prominence of the abstracted data quality indicator over the data in the pop-ups would support different behaviours of participants. Those in the abstracted groups had the metadata continually present, still requiring adoption in the decision process but with minimal barriers to do so. Whereas the detailed metadata groups demonstrated early task phase behaviours checking the pop-ups for metadata were abandoned quickly due to the time pressure. Also, participants indicated how they checked a small number of pop-ups early in their task phase for the metadata. These participants assessed that they had seen enough to assume all the data in the tool would be sufficiently good for them to use in their decisions. The click interaction logs of the tools showed how there was no significantly greater use of pop-up headers from any tool version. This suggests, along with the observed behaviour in the task phases, that abstracted metadata groups weren't returning to check data quality of specific datasets any more than other groups were searching for information in headers.

Russell et al. (1993) highlighted how the main cost in the sensemaking process is data extraction, and by broadening the information space even more with detailed metadata the tool added to this cost. The space was larger and the time taken to extract and interpret was greater. On the other hand, the abstraction reduced the cost of data extraction. The way groups used it to discard datasets or negotiate decision points demonstrated how a shift in representation reduced the time consumed to consider the same dataset.

Across the datasets, the trust scores for non-metadata groups were more often closer to those of the detailed metadata group than the abstracted groups. Though the detailed metadata groups could choose to abandon the metadata they were given, and effectively use the tool the way that non-metadata groups did, the scores show a decreased trust in the data compared to the control non-metadata groups. This may be contributed to by the greater degree of information overload and apparent task complexity and time pressure that detailed metadata introduced.

With the perspective of this data trust influence of metadata, the most interesting results are where the groups from all tool versions had the greatest levels of agreement in their scores. On the car parking and nearby bus stop data all groups shared some of their highest levels of trust. Contrary to differences of around 4 points for data such as volunteer staff requirements, these two datasets had an average trust score rating difference across the tool versions of just over half a point. The justifications in the focus groups may explain the strength of this agreement. The trustworthiness of these two datasets seemed to be influenced strongly by participants perceptions of ease of accurate data collection and ability to verify. The sentiment shared by nearly all participants across all 3 tool versions was that it was easy to count car parking spaces, and they could hypothetically easily go outside in this scenario and check where the bus stops were. They couldn't see how someone gathering this data could do so incorrectly, or that a body such as the local council wouldn't know where their bus stops and parking spaces were. This perceived ability to ground truth a dataset seemed to overcome presentation style or lack of metadata to receive two of the highest trust ratings for each group and tool version. Trust in these relatively static data types were strongly influenced by non-expert preconceptions as opposed to the predicted data types such as operation costs or vaccination throughput which saw greater disagreement in trust scores. Participants that had lower trust in these perceived static datasets were in a minority, voicing scepticism or hesitancy to rate so highly such as the ambiguity of what was meant by "nearby" and competition for parking spaces between vaccination recipients and other site or area visitors. Trust influences are explored more in the next section. This strength of trust in datasets independent of data quality indicators highlights a risk and opportunity for lower or more variable quality datasets.

6.2.2 Elicited factors that impact trust in data

The findings of the focus groups and observations of how groups navigated the task elicited several factors that impacted their trust in the datasets. These were:

- Perception of ease of accurate data collection
- Experience or familiarity with the data type
- Perception of data sources
- Perceptions of ability to accurately predict the data
- Perceptions of objectively correct data

In making sense of the data that they were presented with, participants within groups negotiated the truth of what they were given. They discussed to different extents the quality of the data they had to hand, and whether and how to use it. In some instances, this was to take the data at face value for the sake of the task and given the time pressure, in others they incorporated their assessment of data quality, and how much they trusted that dataset, into their decision process. The trust in data and decisions for collaborating groups is of particular interest in understanding complicated spatial-related long-term decisions and the sensemaking processes (Suprapto et al., 2015). When faced with uncertainty, decision makers may use data of variable quality, where it can be supported with understanding of these trust factors, that use could be avoided. Chorley et al. (2012) presented results from a web-based study that assessed the effect of Twitter metadata on decision makers. Decision makers calibrate their trust in a data source by reference to its agreement or disagreement with other sources of data, and with their own beliefs.

The previous section described how groups agreed on a high degree of trust in the car parking and bus stop data, attributing it to their perception of how easily someone else could accurately collect the data. The sentiment was nearly unanimous that car parking space counts for a site was a highly trustworthy dataset. The participants in each group agreed that it was an easy set to collect, counting spaces, and for someone to check. The same held for bus stop locations, or bus stops and their associated routes for each site. This dataset was presented with a purposeful degree of uncertainty under the heading "Nearby Bus Stops", with no clarification of what qualified as nearby. In the same way as the car parking, most participants trusted that a local council would know where their bus stops were and most believed that these couldn't move, adding further trust to the dataset. There was some discussion about the ambiguity of nearby, and which spaces counted towards the dataset, if it accounted for roadside parking and other car users at the sites. This was only between a handful of participants.

To a lesser degree, but in a similar way, the participants' experience or perception of the generation of a dataset negatively influenced their trust scores. The financial figures, preparation and operation costs, and the volunteer staffing numbers were scored in this way. The majority of the groups were hesitant to fully trust the cost figures, citing personal experience and the notion that "nothing runs to budget". Likewise, volunteer figures were questioned as some participants had experience working with or as a volunteer and were sceptical that a group planning this early in a pandemic would know accurately how many volunteers would really be needed. This had a smaller negative effect on the trust scores to the positive impact of belief in peoples' ability to count parking spaces and bus stop locations. Something that may explain this is how groups handled the certainty or uncertainty in data. For the sites that they were fairly certain of, they took all figures at face value to use in their decisions. In the cases of uncertainty in data, the participants using cost figures, important for them to stay in budget, agreed ways of choosing a figure to work with. For most groups this was to take the highest figure in the range presented, the upper bound of costs, assuming a worst-case scenario without generating their own cost estimates. This small exercise may have created a positive trust impact on that dataset, counteracting some of the negative impact of the uncertainty and distrust they had in budgets and cost projections.

This idea of trusting certain types of data that participants felt a source should or would know accurately also carried through to some of the sources in the tool. The census, even though from 2011, carried weight as a trusted source for most participants, and was therefore a reasonably trustworthy dataset. Only a couple of participants noted a concern about the potential age of the dataset. The World Health Organisation, another established source, brought trust to the vaccination site data presented.

The datasets described so far that received relatively high trust scores and agreement across participants could be described as static or historic data in terms of temporality. Participants were more hesitant to trust data that would be predicted or modelled. They assumed in this fictional region that there hadn't been another pandemic recently, and raised questions about the ability of someone to accurately predict data such as required staffing, vaccination throughputs, and site costs. These, being predicted data on unfamiliar phenomenon, were not readily verifiable by the participants or the fictional data sources the way that participants saw car parking spaces as being easily countable and checkable.

The opinion of objectively correct data carries through from the above points. In addition to the perception of ease of accurate data collection, groups demonstrated presumptions that a dataset just is correct. Notably the data presented on the map in the tool, the spatial-visual data, was unquestioned. This isn't a new phenomenon and is returned to later in this chapter. Participants did not question the accuracy or hesitate to trust the visualisations they were using in their decision process. Some groups relied heavily on visual cues in their strategy, and indicated desires for further visualisation such as demographic heat maps.

In addition to these preconceptions and sentiments towards different types of datasets, many of the groups exhibited trust building behaviours while exploring the tool. These acted mostly to reinforce the level of trust they were assigning, their comfort to use the data in their decision making, rather than to disprove or counter their feeling. Participants would suggest a pattern in the data, voice to their group, and then seek confirmation. For example, most groups looked for relationships between the site and the demographics of the population in each catchment to try and streamline some of their strategy. A participant would suggest where the elderly population may be, then look at figures for a couple of sites in each area to see if they fit the hypothesis. In a similar way, participants would link facility types to site costs, enabling them to filter the site quickly based on that factor. Where participants were hesitant to use data initially, they often sought to adapt to be able to use it in their decisions. This was most prominent with cost data. Across all tool versions the groups were hesitant to fully trust the data, particularly as it was presented as a range, but they were aware it was a critical factor in their decision and proposal given the budget constraint. The majority of groups adapted by taking the upper bound of the range, assuming a worst case scenario, enabling them to be comfortable using the data in the decision process. One group used the lower bound, citing a desire to make the numbers fit the best.

These factors discussed above were independent from the tool version groups were using. With the general behaviours appearing across all groups. These indicate the potential strength of preconceptions and experience of non-experts on trust in or adoption of data during decision making. The near unanimity in high trust of parking and bus stop datasets, and scepticism of budget and cost data, embodies this.

Single values received face value acceptance more readily than ranges, then were further augmented by the perceptions of individuals already discussed. Ranges suggested uncertainty to participants, but the upper bound heuristic enabled them to mitigate some of that uncertainty. Ambiguity was noticeable in the dataset using words, the accessibility rating good or poor. Text values were more easily noticeable in datasets that were mostly numeric, being the anomalous “No Data” entries. On the other hand, erroneous numeric values were less readily spotted outside of the abstracted metadata version of the tool. The traffic light system gave an additional dimension of data without significant additional mental workload or exploratory work needed to find quality information.

When considering how these factors feed into the support of decision making for the groups, Dervin (1998) presents a useful summary of the participant behaviour, “when users are evaluating answers from knowledge sources that they found not useful, they focus on system criteria (e.g. credibility and expertise) but when they evaluate answers they found useful they turn to time-space-movement (e.g. getting new ways of looking at things, unearthing causes, moving toward destinations)”. Each time a participant comes across data they aren’t finding useful, they may focus in on credibility, and the trust factors this section has explored. Understanding these factors means that the risk or potential cost of a user finding the data source not useful could be anticipated.

6.2.3 No difference in task performance and decision confidence providing abstracted metadata and no metadata

The results showed no difference in the task performance and group confidence in final decisions when provided with abstracted metadata and no metadata. Groups given detailed metadata showed significant differences in comparison to the other two conditions, reductions in both task performance and confidence in their final decisions.

Comparing the non- and abstracted metadata conditions, the results are not identical but showed little separation based on the metrics they were evaluated with. Group 1, a non-metadata group, performed exceptionally well. This may be explained based on their higher self-evaluated technical literacy and strategy game experience when compared with all other groups. Their results are not excluded on this basis but can be taken into consideration when comparing the groups in these two conditions. The other two non-metadata groups performed much closer to the abstracted groups. Using the dimensions of the proposals and outcomes as metrics for performance, the use of the budget, number of sites selected, allocation of staff, and vaccinations distributed, the top 6 spots were split across the non- and abstracted conditions. With group 1 providing the best performance, the next spots alternated between an abstracted condition group and non-metadata group. Meanwhile, detailed metadata groups made up the bottom 3, with performance on some metrics an order of magnitude worse than the other conditions, notably the vaccinations delivered. Groups in the detailed metadata condition demonstrated the highest levels of task freeze and changes in decision process throughout their task phases. It’s suggested that these groups experienced the greatest degree of information overload, and subsequently experienced the greatest feeling of time pressure over the duration of the task, adopting and changing decision processes in response to the diminishing time. An indicator of the information overload can also be seen in the regularity of switching processes in the detailed metadata groups. These groups shifted and abandoned task approaches and data recording approaches (e.g. handwritten notes and spreadsheets) more than the other groups, reflecting attempts at representation shifts by the group to find data and data properties that were most relevant to the task and retrievable to help them solve the problem (Russell et al., 1993) With regards to task performance and errors, one group from each metadata condition made a constraint error in their proposals.

Non metadata and abstract metadata groups chose, on average, more sites in their proposal during the same task time, with detailed metadata groups choosing much smaller proposals. Most variables linked to the number of sites chosen while staying within budget. Staff allocation reflected the number of sites chosen, fewer sites meant lower staff requirements. Cost behaved in a similar way, highlighted by the scale of the budget unused by detailed metadata groups, around half for some. In a competitive environment, where there are team members with information that others don't have access to, like this pandemic response team, it was found that the less competent individuals shared more information. However, decision accuracy was only better under a cooperative environment (Dayeh and Morrison, 2020). This scenario was not a competitive environment, but the introduction of detailed metadata hampered cooperation due to overload at an individual level, constraining their performance.

Returning to the performance of group 1. The potential effect of their technical literacy and strategy game experience was apparent in observing their task approach and team working style. They were the most cohesive group in the study, and their iterative process that moved between constraints at increasing granularity quickly offered up workable proposals. Their approach worked in this scenario and with the datasets designed for this study, but they would have faced more limited success if the data quality was lower or more varied, and if the decision outcome calculations were adjusted closer to worst case scenario. In particular, the cost figures worked within budget for them because the outcome calculation took the midpoint of the cost ranges. Non-metadata groups used the highest number of sites in their proposals that had erroneous data designed into them, meanwhile abstracted condition groups used the least of these sites. Discussed in the previous subsection, the traffic lights helped groups more easily identify erroneous or anomalous data.

Proposal confidence levels in groups were highest in the non-metadata condition, but not significantly different from those in the abstracted condition. Detailed metadata groups were least confident in their proposals. It's suggested the strongest influence on these ratings is the feelings of time scarcity experience by the teams, and subsequently the decision approaches adopted and extent to which these were carried out. Notably, the detailed metadata groups had confidence scores of below 5/10 on average. This suggests a detrimental effect of presenting them with the detailed metadata in addition to the already significant amount of data in the tool. This appears to be mitigated by the abstraction offered in the data quality traffic lights.

Surprisingly, the confidence scores don't correlate to the data trust scores already discussed. Groups with high trust in the data didn't demonstrate significantly higher confidence in their proposals, nor did groups sceptical about the data presented show significantly lower confidence in their decisions. More work is needed to understand this lack of correlation, it is suggested that any link is being suppressed in this scenario by the time scarcity of the task. Most groups cited more time as the main factor they would change to improve on the confidence scores they gave in the focus groups, wanting to spend more time checking alternative proposals and understanding the data. They wanted to feel like they'd had enough time to complete the task as well as they could. It may be that in scenarios beyond a certain threshold of time pressure, the trust a group has in data they are using doesn't have an influence on their confidence in decisions made. It could be valuable to understand under what time pressures engendering more trust in datasets will or won't have significant impacts on the confidence in the decisions made with that data. This finding does suggest improving trust in data won't increase confidence directly, but combined with other findings discussed so far it suggests that decisions support systems and the presentation of the data can be done in a way to not add to the feeling of time pressure for decision makers.

6.2.4 Abstracted metadata encouraged greater data quality assessment and trust building behaviour

In addition to helping participants identify erroneous data within the tool, the abstracted metadata, traffic lights of data quality, encouraged a greater number of participants to consider the quality of the data they were using than the other study conditions.

The visual data quality prompt, persistent throughout the tool, kept the idea of data quality nearer the forefront of participants' minds during their decision process. The groups in the abstracted condition showed greater instances of questioning data quality while they were comparing sites for their proposal than seen in the non- or detailed metadata groups. The data quality questioning behaviour of the other two conditions was about the same. Detailed metadata participants mentioned initial use of the dataset headers and scanning of quality metadata, but quickly assessed the quality as sufficient across the tool to ignore for the rest of the task phase. Further questions only arose around clearly erroneous data points. Whether explicit or not, these visual prompts were used by groups orienting through their communication, helping maintain a common operating picture by sharing aspects such as what they were noticing, bracketing, presuming, and doing (Weick et al., 2005). Cognition was residing in team interactions (Cooke, 2015). The abstractions contributed to this communications. The design of the datasets for this scenario meant that groups weren't really penalised for using lower quality data in their decision process or proposal. This should be explored further with more varied quality data, in this case it was generally good quality. The exclusion of a site that would penalise a group was mostly done not on the basis of the low quality data by non-abstracted groups, but for other reasons, so the effect is unclear. The observations of the group discussion did reveal the potential for issues with lower quality data. Groups not in the abstracted version were more comfortable taking data at face value, even arguing the apparently anomalous data that could be an error was beneficial to their proposal and included in the tool by the researcher and therefore could be used in their proposal. Under a greater range of data quality or prevalence of bad/low quality data it's suggested that abstracted data quality metadata would come into its own, with a greater effect, and mitigate against the behaviours and data adoption in the other conditions. Future studies need to explore if benefits are seen in this way in more varied datasets, and what ratios of data quality level demonstrate differences in decision outcomes. Lack of data literacy creates a problem with the rising usage of inconsistent quality data in strategic decision making (Xing and Wang, 2021), the abstraction helps lower the barrier of data literacy, guiding users in interpretation of data quality. Research has shown that provision of quality metadata along with its associated information results in different decision outcomes to when the decision is made using the relevant information alone (Dijkstra, 1999). The outcome here isn't decision performance but the trust in the data, and potential for improved outcome performance if the experiment scenario used data of a generally poorer quality.

Presenting data quality metadata, either in abstracted or detailed form, functioned as a reminder to groups that not all data was trustworthy, and they shouldn't necessarily take it at face value. A degree of caution was instilled. They took some time to judge the datasets, more for the abstracted condition, then continued the task with this sense of data quality. The metadata could be considered an anchor in the sensemaking process (Klein et al., 2007). Though used to the benefit of the groups here, people normally limit the number of anchors they use to just a few, the additional metadata takes up one of those slots. Help in tracking available anchors could be considered to alleviate this while also providing the benefit of the data quality metadata. The lower degree of data quality assessment in the detailed metadata groups may be explained by a combination of the time pressure and the design of the metadata for the study. The time pressure and additional information to process meant participants were more likely to seek most relevant data for their decision process, discarding metadata that may initially feel superfluous or too much to process in the timeframe. Additionally, the detailed metadata reflected the generally good quality of the data designed for the tool, with relatively high accuracy and completeness percentages across the board. This design meant that participants checking a few datasets early in the task phase were quick to assess the data as reasonably good and assume this applied across the tool. One participant indicated how they'd have been more careful if any of the values they saw were substantially lower. This suggests some work on exploring thresholds of data quality and acceptance for use by different users could be beneficial.

6.2.5 Opportunities and risks for abstracted data quality metadata in decision support system development

The observations and findings of this non-expert novice use of the decision support tool in the medium time pressured group scenario offer a number of opportunities in application and further research of abstracted data quality metadata.

Taking the nature of the influence of abstracted metadata on participant trust in data, a key point that arises is the burden that is placed on the activity of choosing thresholds for data quality. The ease of discarding sites with red data indicated how the abstraction lost some nuance but increased the usability of the metadata for these participants. For the groups in that condition, the burden of understanding the dataset and developing trust was outsourced. The opportunity to provide influential metadata without the negative effects of detailed metadata also brings risk. Participants didn't demonstrate interest in where or how the thresholds were arrived at, they adjusted their decisions around the colours they were presented. The abstraction is readily adopted as it is intuitive (Shankaranarayanan and Zhu, 2021; Devillers et al., 2007). The group that discussed the significant trust they put in the data attributed a portion of that to the researcher that provided them with the tool and datasets. Trusting that source, they trusted that the data they were being given was good to use. Together, this indicates a need to not just explore further how the thresholds are constructed, but the effects of the authority providing the data on the extent of the influence on data trust. Klein et al. (2007) describe how “data fusion algorithms post opportunities to reduce information overload but also pose challenges to sensemaking if the logical bases of the algorithms are underspecified”. The metadata abstraction presents a method of reducing information overload, but the process to reach the thresholds and abstractions needs sufficient understanding to avoid negatively impacting the sensemaking process and decision makers.

The process of constructing the thresholds is resource intensive. Each dataset is different, and so in this case the thresholds for low, medium, and high quality were bespoke. The activity requires a degree of expertise and understanding of the dataset for someone to make a judgement call or apply a series of rules. There is an opportunity to reduce expense of this process using algorithms or machine learning. However, this requires further research in both the process of making the thresholds, and in the perceptions of data users if they know how or where the thresholds were applied. People or programmes preparing the thresholds may not be interested in the group performing well, this doesn’t mean they will act maliciously, but could still have an effect on the outcome of the task.

While the threshold process is resource expensive, there may be success in prioritising the use of abstracted data quality metadata to certain datasets. Rather than all data being presented with abstracted metadata, purposeful use of data quality made reap benefits for decision makers. This certainly needs more work to identify the best areas to target, but the factors elicited in section 6.2.2 show considerations that could be made when identifying opportunities. The designers of the decision support tool, or data brokers, could choose to augment the decision maker trust in data that is likely to have the lowest level of preconceived trust. In short, boosting the trust in a dataset that users may otherwise be hesitant to include in their decision process. Conversely, the same action could be applied to datasets that users are likely to misplace strong preconceptions of trust in. This could prevent or lessen the chance a group places too much significance on a dataset of questionable quality in their decision. Well-placed visual data quality indicators could help non-experts in identification of erroneous or anomalous data, or instil caution where appropriate rather than values being taken at face value. Priority could also be given to certain data types, for example predicted data. It is worth reiterating the burden and responsibility this places on a person or organisation. It is unclear where the responsibility lies, or more likely to what extent the responsibility lies with data owners, data brokers, decision support tool designers, and others involved in the tools and data used by groups in these scenarios.

It would be worth exploring the area of this research in other settings, such as with expert decision makers and in different time pressures. These factors are expected to influence the adoption and use of the metadata by the groups and the processes they employ to complete tasks.

The decision processes were explicitly chosen or evolving across each group to varying degrees. 5 different approaches were characterised from the participants: bottom-up building, top-down pruning, spatio-visual, subgrouping, and erratic/unstructured. In the abstracted condition, groups were observed using the red or lowest quality data as reasons to prune, to discard sites from consideration either on the global scale or between a handful of candidate sites. There is an opportunity here to see how presenting an abstraction of data quality influences the decision process adopted by a group of decision makers. The attribution of traffic lights, easy to parse in the time allowed, could nudge groups into certain methods depending on the distribution of high, medium, and low quality data. For example, the discard method works well if there is sufficiently good data in general, with a smaller number of highlighted low quality data points that can be used to prune. It is expected that if the ratio was flipped, the groups that discarded low quality data sites would need to change their decision process otherwise propose just a few sites at the end of the task. Knowledge of established or guided decision processes could work in parallel with this. The participants in this study weren't instructed on how to arrive at their proposal. However, there are many established formal decision processes to follow. These could be assisted with targeted use of data quality metadata. This returns to the point of further research in different time pressure scenarios, as each has its own examples of established decision processes.

The findings of this study suggest a need to explore the boundaries of the strength of abstracted metadata. Cost data was discussed as a dataset that all participants, regardless of tool version, were hesitant to trust fully due to experience with inaccuracy of budgets and projections. The results suggest that highlighting these datasets green could have boosted the trust from participants. However, it is unclear if, or at what point, perceptions and experience of trust in a dataset overcome presentation of abstracted metadata. Is the green highlighting sufficient to counteract the scepticism of data users? This same point stands for the datasets that have high trust due to the perceptions of easy and accurate data collection, such as the car parking. It is equally unclear at what point amber or red highlighting could influence user data trust over preconceptions of static physically-verifiable datasets.

Finally, further work could explore the relationship between the type of data and the level of preconceived or embedded trust for experts and non-experts. In this case, results suggest that static or historic data has higher trust inherently for these non-experts than predicted data. Not explored in depth in this study were the attitudes towards live data. With better understanding of any relationship here, it may be possible to identify more easily the target or priority datasets for metadata abstraction as discussed above. Perceptions and inherent trust or distrust could be anticipated and accounted for.

This matters because the findings have shown a way of engendering trust in datasets for group decision makers in a way that doesn't degrade task performance or increase experience of time pressure. This abstraction method is not new, employed in other fields such as nutritional labels for consumers, and its ease of use could help avoid use of low quality data or high trust in a dataset that is perceived as easy to check but is not necessarily correct. The groups often cited priorities of data as being cost and population, but a lot of them easily dismissed or made sub-decisions between sites based on data in the transport tab (car parking, bus stops, accessibility). This tab was designed to be almost superfluous, adding to the volume of data presented in tool and the feeling of time pressure, but was leveraged to dismiss or select sites with the same weight as datasets such as population coverage to be vaccinated.

6.2.6 Confirmation of the power of the map

Mentioned in section 6.2.2, regardless of tool version, participants hardly questioned visualisations on the map, whether it was the population catchment circles, bus routes, or icons representing cost ratings and facility types. This isn't unexpected or a new finding (Wood and Fels, 1992; Monmonier, 2018), it reinforces in this tool, scenario, time pressure, and group setting that the power still holds. It directs to a continuation of the work by Devillers et al. (2002, (2007) on visualisation of data quality on the map. The paper suggested a way of providing spatial data users with abstracted quality ratings in the same way this study does, but doesn't explore the effects of it on the decision makers. The findings in this study suggest positive effects could be found recruiting the abstracted metadata on a map, however there is potential for visual cluttering that could confuse non-experts in particular, detracting in similarly time pressured situations. It would be worth seeing if these findings can be replicated on visually represented spatial data under the similar group and time settings.

A key reason this research is needed is the list of desires indicated by many of the study groups. Participants wanted access to visualised demographic data, heat maps and overlays that would help them visually understand where the population was and how it was made up. Taking the power of the map, it is expected that the constrained trust in population and catchment figures in this study wouldn't translate to the visualised population data. Instead, it's expected that the same data, presented in a heat map rather than table below the map, would receive a higher trust score and be used in the decision process with a more inherent sense of trust.

There is a risk trying to present the abstracted metadata on the map for visual clutter or confusion that would reduce the benefits of presenting the data quality. In terms of transferability of findings, it would also be valuable to study this aspect of the abstraction and power of the map under varying time pressures to see how the interpretation and adoption of data quality metadata in the decision process changes. In the way visualisations could have the same effects as data presentation choices in the tables, such as ranges highlighting uncertainty and fuzziness or softness of edges on a map can do the same, presence of a small ratio of striking highlights may highlight particularly low quality or anomalous data the way red figures in the tool tables did.

The visualisation method suggested by Devillers et al. (2002) for spatial representation of data quality metadata, the traffic light abstraction but on the map rather than the text, provides a good opportunity to test if the findings are transferable from this study. Study 2 is a scenario that uses a map-based tool and shows the text-colour-based abstraction working but doesn't present data quality information on the map. This needs to be explored, though there is an anticipated risk of visual colour clutter, particularly for novice or inexperienced users. The power of the map was confirmed in the observations of study 2, the lack of questioning of data presented on the map in the tool and the spatial-visual aspect to the group decision making, but the risk here is that non-experts could be overwhelmed by the visualisation.

6.2.7 A return to study hypotheses

Returning to the study hypotheses,

1. Groups and participants that are provided metadata of either abstraction will have greater trust in the data used in the decision making than those without and, as a result, greater confidence in the decision made than those without.

The effect on trust was observed only in the groups provided with the abstracted data quality metadata. The groups provided with the detailed metadata diverged from this and showed lower levels of trust in the data in the tool than the control groups that had access to no metadata. No evidence of the second half of the hypothesis was found. The confidence in the group proposals at the end of their task phase did not correlate with the trust levels in the data used to arrive at the proposal. The confidence was noticeably lower in groups that used the detailed metadata, this may be explained by their greater experience of time pressure. Feelings of time pressure and ability to adequately explore proposal options appeared to have the strongest influence on the group decision confidence. Abstracted metadata didn't reduce the feelings of time pressure in groups, in comparison to the control groups, but it didn't increase the feeling. This may explain why the confidence levels in the non- and abstracted metadata groups were roughly the same.

2. The groups using detailed metadata will experience the greatest time pressure in their decision making, and exhibit less methodical decision processes and interactions between members. The groups using abstracted metadata will experience the least time pressure.

As described above, the first part of the hypothesis was observed but not the second part. In the observation of participants and discussion in the focus groups, it was apparent that those using the detailed metadata tool experienced a greater degree of information overload and with that a greater sense of time pressure. The most unstructured or changeable decision processes were observed in the detailed metadata groups. This appeared in the frequency that groups adopted and changed methods of selecting or discarding candidate sites. It appeared to be a function of the time pressure that groups would try to change approach looking for a faster way to assess the data and generate a proposal. The interactions between team members were not as linked to the metadata abstraction. Interaction levels didn't seem to be a function of the decision process being used. The second half of the hypothesis is rejected, it was not apparent that abstracted condition groups experienced less time pressure, they behaved and reported similar feelings as the non-metadata groups.

3. The abstracted metadata groups will produce the best decision outcomes, the detailed metadata groups will feel as confident as the abstracted metadata groups but produce the worst outcomes.

This hypothesis is only partially accepted. The detailed metadata groups produced the 3 worst outcomes from their proposals, but did not demonstrate confidence levels as high as the other conditions. The abstracted groups performed as well as the control non-meta groups, producing similar results from their proposals and with similar levels of confidence in the decisions they made. It is suggested from the findings that this distribution of performance is partly a result of the data design in this study, that the overall quality of the data available to participants was relatively good, and there were minimal penalties for using low or medium quality data. Additionally, it's suggested that under conditions that have a different distribution of data quality, the abstracted metadata may produce significantly better decision outcomes.

These findings indicate an importance of decision support system designers to understand the group expertise and to be able to anticipate which datasets may have built in or preconceived notions of trust or distrust. This understanding could better inform design of overall systems, and implementation of abstracted data quality metadata.

Groups didn't necessarily prioritise use of data that they trusted more in making their decisions. Population figures weren't the highest trust score but featured strongly in the site selection. There are acceptable levels of trust to incorporate or not discard data from a decision. In a similar way, high trust didn't indicate prominence in decision making, data like the car parking figures were incorporated by groups dismissing sites, but not a main driver for forming their proposal. This relationship suggests to some extent why the trust scores and decision confidence scores aren't as closely linked as expected before running the study.

Further work could also be carried out on the effects of iterative or extended decision making. This was a single time limited task and didn't explore whether the effects of metadata abstraction change over iterative or repeated use by the decision makers. With more experience, non-experts and teams would become more familiar with the capabilities of the tool, the data, and their working process. This may augment the findings if in this scenario the pandemic response team were to review a 1 month outcome, and be offered the chance to make changes to their plan for the next stages.

The artefact use in this study showed the desires groups had for functionality in the tool. Most notably participants wanted the ability to customise their tool view more, sorting the data presented into formats that supported the decision process they wanted to use. This included site comparison views, data sorting such as selected sites by cost, and control over the volume of data being shown in the interface. This level of customisation can be at odds with the design of decision support systems. In this study, the tool is bespoke and design choices were specific to the study and scenario. This point is included to note how participants, decision makers, will fit the tool or additional artefacts to their desires to support how they want to carry out their sensemaking and decision making process. It follows the suggestion of abstracted metadata being applied while anticipating user perceptions of datasets; design of the interface with knowledge of the decision context and data can help anticipate the interactions users will seek or benefit from.

The next chapter combines this discussion with the reflections on the exploratory study to present the conclusions of the thesis.

7 Conclusions

7.1 Summary

Decision makers have rapidly increasing quantities of data available to them to drive their strategic decision making. The proliferation of sensors, IoT, and data storage options add to this continually. There are huge volumes of this data, and it is inherently messy. There is a need and opportunity for decision makers to be able to assess and use the quality of the data they are incorporating in their decision processes. The exploratory study in chapter 3 demonstrated real world decision makers faced with uncertainty around the data they were using, while chapters 5 and 6 showed results from an experimental study that tested a method of putting that capability into the hands of decision makers. This chapter revisits the research questions set out in the introduction of this thesis, before articulating the contributions the research has made. Some limitations of the findings are then discussed, before offering a number of avenues that further work could take to build on the conclusions set out.

1. To what extent is data used in the group sensemaking and decision making process for significant development projects?

This question was approached by the exploratory semi-structured interview study carried out with project management groups for university capital projects.

These capital projects and their management groups offer significant opportunities for greater data usage in a team sensemaking and decision-making environment. In cases that data were made available to the group, there were commonly issues with what was available, issues of accuracy highlighted by the example of future occupant lists changing throughout the project that were still incorrect at the point of move-in. In many cases there was a desire for data from participants to enable them to test assertions or decisions being made.

In most examples reported by the participants the data used in discussions and arriving at a decision were not interactable. The presentation and visualisation methods made it difficult to interrogate the data or test any assumptions, and this contributed to some ambiguity for members as to the purpose of the PMG and the decisions it was able to take during the project. Though some tools for interacting with data were available in meetings such as the tablets being used to follow the reports, consideration should be given for this interaction by individuals and the team and the impact on the collaborative sensemaking process.

One of the projects demonstrated that ambiguity in data impacted the decision-making process, reducing the confidence or satisfaction in the final decision. This asked the question of how transparency with the fuzziness or the veracity of data can change the confidence in assertions from the data and the decisions reached? There is potential to achieve increased satisfaction in decisions made through enabling deeper questioning of assumptions and data.

Trust can be engendered in data sources used during the sensemaking process. From the examples of student occupancy and timetabling in the interviews, this trust could be engendered through provision of metadata, highlighting characteristics such as provenance, allowing the individuals to make assessments of the data quality. What then would be the impact on the confidence of individuals and the team making these decisions and communicating them to stakeholders?

The spatial-related context offers an opportunity for richer presentation and visualisation methods for data, which could better support the sensemaking process and decision making for the team. In a multidisciplinary team setting, with varied expertise and perspectives of decision makers, how does an increased accessibility to and interaction with data change how people perceive the data as a tool for decision making? In what way does awareness of different characteristics of data affect the perception of validity and veracity, and the trust in data for use in the discussions?

In settings such as the projects explored in this study, a team needs to achieve consensus with these multiple sources of data and their individual perspectives. They need to be able to interact with the data, assess its quality and interrogate assertions, ultimately establishing trust in some of the data, reaching a shared state of situational awareness, and making a decision. Some of the most granular decisions such as furnishings were made with the most autonomy as a group, with use of financial and construction program data of the project to understand the ramifications for decisions. The largest decisions that were made by the group involved the most interaction with related groups and an extended series of approvals. These showed a much broader consideration for the strategy of the university, the motivation for the project, and the building in relation to its locality on the campus. For capital projects with institutional framing to the complex team decision making, there is more work that can be done to understand the relationship between the granularity of decision and the decision process. This would direct the sensemaking support requirements for these such as data treatment and presentation.

2. What are the similarities and differences in the team sensemaking and decision making process under different time pressures?

Explored in the literature already, this question fell out of the exploratory PMG study with an interest in the targeting of interventions and transferability of findings. The question is not explored fully due to time constraints of the research period, instead a framework is offered in figure 3.1 in chapter 3 that could help identify and compare decision making scenarios in relation to the temporality of both the decisions being made and the data being used. This framework needs validation, but from this, a single time setting was used in the experimental study that tackled the third research question. In discussing the types of decision making settings, and characterising them by the time pressure and prevalence of datasets of different temporalities, this product of research question 2 provided a steer for the final and main research question the thesis focuses on.

3. What is the effect of presenting metadata in team sensemaking as part of the decision making process?

This question is addressed under a specific setting, with a map-based decision support tool offering an abstraction of data quality metadata to teams under a medium level of time pressure. Medium here being a period of just under an hour allocated to participants to complete a task in the experimental study. The specificity of this scenario is discussed in acknowledging potential limitations of the findings later in this chapter. The shift from the lower time pressure of the groups covered in the first study provides some awareness to support generalisation of findings beyond the setting in the second study.

The experimental study, testing a technical intervention, demonstrated that presentation of an abstraction of data quality metadata improved data trust while removing the negative effects of introducing metadata to this time pressured context, but didn't improve on the decision outcomes or decision confidence exhibited by groups that didn't receive any data quality metadata. The abstraction significantly improved the trust in the data used during the decision making against both the control (non) and detailed metadata groups without detrimental effects to decision outcomes. What the study showed is that this traffic light abstraction of metadata (in this scenario) mitigated effects of adding metadata to the group decision making process, while also improving trust in the datasets and facilitating decision outcomes and confidence at the same level as groups with no metadata. There was no clear difference seen in the confidence in decisions for groups with abstracted or no metadata. This result is unexpected and is discussed as part of the further work later in this chapter. It is proposed this is a product of the study design, and the generally good quality of data used in the scenario. The abstraction from detailed data quality metadata such as provenance, completeness, and accuracy to traffic light indications of low-, medium-, and high-quality data demonstrated a working method of engendering trust in data.

The study also elicited a number of factors that impacted the trust in data:

- Perception of data sources
- Experience or familiarity with the data type
- Perception of ease of accurate data collection
- Perceptions of ability to accurately predict the data
- Perceptions of objectively correct data

In making sense of the data they were presented with, participants within groups negotiated the truth of what they were given, to different extents discussing the quality of the data they had to hand and whether and how to use it. In some instances this was to take the data at face value for the sake of the task and given the time pressure, in others they incorporated their assessment of data quality, and how much they trusted that dataset, into their decision process. The presentation of abstracted data quality metadata encouraged greater data quality assessment and trust building behaviour than the other two conditions. The traffic lights functioned as a reminder to groups that not all data was trustworthy, and they shouldn't necessarily take it at face value. A degree of caution was instilled. They took some time to judge the datasets, more for the abstracted condition, then continued the task with this sense of data quality.

The factors listed above, combined with examples from participants, indicated potential for anticipation of trust perceptions, and with that, anticipation of areas or datasets to focus on. This focus could help strengthen trust in a dataset more and add depth either to help or encourage trust, or could limit or avoid misplaced confidence in uncertain data. As an example, projected or future data such as polling data presents a case of often over attribution of trust.

Reflecting on the motivation of the research in this thesis, the challenge of helping decision makers navigate large volumes of messy and potentially untrustworthy data, these findings suggest an opportunity to support the strategic decision making in contexts such as smart cities and campuses. In considering how to enable the smart cities of the future, the streams and large scale of data being part of what makes city smart needed considering. The decisions that groups like policy makers, planners, and emergency response teams make mean it needs to be accessible to a range of multidisciplinary groups in a variety of time pressures. Domain experts aren't necessarily experts in all the data and decisions that will be put in front of them.

Considering the spatial or place-related aspect of this research, the findings of the map-based tool show the intervention working in that context. The role of the map and opportunity for further research is considered later in this chapter, the abstraction was in the colouring of the text rather than of the mapped data. Participants in all groups in the second study demonstrated degrees of spatial thinking and decision making, navigating the tool and shaping their proposals with the presentation of the options on the map. There were few questions about the veracity of data placed on the map in the tool as opposed to the data in the tables below. As discussed in chapter 3, the discussions and decisions of the management groups were grounded in a series of spatial granularities that reflected the focus of the meeting, at a room, building, campus, or city level.

Given the opportunity, people want to make decisions using data they trust. Metadata can engender this trust if the decision makers have the capacity to use it. Under varying time pressures of decisions, decision makers as individuals or groups should be able to achieve a better sense of understanding the data. Study 1, the project management groups, gave a clear case of people in real world settings wanting to question the data. Meanwhile, the testing of the technical intervention in study 2 highlighted how people can throw out data because they are overwhelmed, either through the volume of data or the scarcity of time. An abstraction of metadata, colouring the text and numbers themselves, enabled decision makers to quickly question and assess the data, filtering bad quality data clearly highlighted red, reaching decisions with higher levels of trust in the data they'd used.

7.2 Contributions

Traffic light visualisation of data and abstractions of data quality metadata aren't new, but this research presents and tests an alternative application of data quality metadata. In addition, this research focuses beyond just the decision outcomes, highlighting the impact of metadata on data trust in the time pressured scenario. The findings have demonstrated the benefit of abstracted metadata in this context and furthered the understanding of the benefits in this time pressured group decision making setting. The abstraction provides a new way to engender trust in data, and this thesis reports the other effects observed presenting the data this way.

The results don't overturn common sense, but contribute a strong reinforcement to findings, and direction for research in the future. Data in decision making is a well-trodden area, though research on putting metadata or data quality indicators in the hands of decision makers focusses mostly on presentation methods and decision outcomes. This research builds on that by presenting the data quality metadata colouring the text/numeric data itself, while comparing the effects on both decision outcomes and decision maker sentiments towards the data and decision.

The studies in this thesis correspond with existing notions in literature around desire for and use of data quality metadata, or data quality indicators. The main study is a qualitative experimental study that reveals some of the factors that influence trust in data, the impact of the data quality metadata on trust, and the impact on the decision outcomes in contrast to adding detailed metadata under the same time pressure. These findings can help inform design of metadata going in databases or being presented to decision makers, in this case non-experts. The research contributes in a qualitative way the agreement across participants on the high trust in spatial and perceived easy-to-collect data, while highlighting the disagreement dependent on metadata abstraction over other data types such as projected datasets.

Through the findings in this research, several additions or updates are offered to existing work that motivated the direction of the thesis as outlined in chapter 2.

Ham, Jung, and Park (2021) offer a conceptual model of the elements and phases that conclude with an output and team decision making performance. Two updates are suggested to the conceptual model. Data as an input and part of the process of decision making seems insufficiently apparent, and it's suggested that the model is updated to include data and its role more explicitly. The elements already included in the model direct the fitness of use for data or evidence driven decision making. Additionally, the model uses arrows with only one direction to link elements in the input, process, and output phases of decision making. The team element relates to the team member coordination while the individual elements relate to characteristics of individuals that can affect team decision making. The observations from both studies in this thesis suggest that this conceptual model should include a bidirectional arrow between the team and individual element to acknowledge the interplay between the two during decision making processes. The two are not static or independent during a team decision, instead forming an updating cycle as team behaviour exerts influence on individuals and vice versa. For example, the individual element of mental state and awareness of roles can be influenced by the group element of communication and decision making coordination throughout a decision process.

Speier-Pero (2019) presents a graphical representation of the expected differences in conditions during a decision making task with limited time availability. This representation, drawing a relationship between the individual, information presentation, and decision strategy, presents aggregation of data with an assumption of data quality or trust in data. The model functions well to give the study hypotheses structure, and the findings that suggest how time pressure can influence how information is processed. The findings in this thesis suggest the need for an additional step, information interpretation, between the individual and information presentation that reflects the ambiguity observed.

Moges et al. (2016) introduces a detailed diagram of the impact of data quality metadata on decision making, highlighting factors that help or hinder adoption of the metadata by decision makers. With the results of the research in this thesis, the model is updated to include a necessary acknowledgement of the abstraction level of data quality metadata, and the influence of data trust. The addition of the data trust node also incorporates the factors elicited that influenced trust in the experimental study and echoes some of the findings of the exploratory interview study such as the individual perceptions of a data source. This updated model is presented in figure 7.1. It's important to note how there is an interplay between the nodes on the model given by Moges et al. As an example, education will certainly impact the perceptions of data sources, and experience interacts directly with data quality awareness.

Price and Shanks (2011) suggested in their protocol analysis that data quality tags "are associated with increased cognitive processing in the earlier phases of decision making, which delays generation of decision alternatives". This wasn't observed in the studies in this thesis, instead it was seen that the abstracted metadata groups carried out the same initial phases as non-metadata groups, both exploring the tool and data first, before suggesting proposals. No delay was observed on the generation of decision alternatives for abstracted metadata study groups.

Phillips-Wren and Adya (2020) suggest that uncertainty is a decision stressor alongside information overload, time pressure, and complexity, and that the moderation of these can enhance decision quality. The findings of this thesis demonstrate this behaviour, that under a fixed time pressure and problem complexity, information overload was a moderating variable while trying to address uncertainty in data. The presentation method of the data quality metadata moderated the uncertainty, and the abstraction didn't degrade the decision outcome while increasing the trust in the data.

Devillers et al. (2002), Shankaranarayanan and Zhu (2012), Shankaranarayanan and Zhu (2021), Shankaranarayanan, Zhu, and Cai (2009), and Watts, Shankaranarayanan, and Even (2009) all explore the visualisation or abstraction of data quality metadata. The work in this paper adds to the understanding in this research area, testing another abstraction in a grounded setting. The findings of the thesis reinforce the idea that an abstracted method of presentation allows for more accessible communication of data quality that could reduce the risk of misuse of data in this scenario. However, the focus is often placed on decision outcomes or performance in these papers. In assessing the presentation of data quality metadata, this thesis recommends that attention should simultaneously be placed on both outcomes and decision maker sentiments such as trust. With a more complete picture of the decision making the interplay of these different elements could become clearer, and risks and opportunities more easily identifiable.

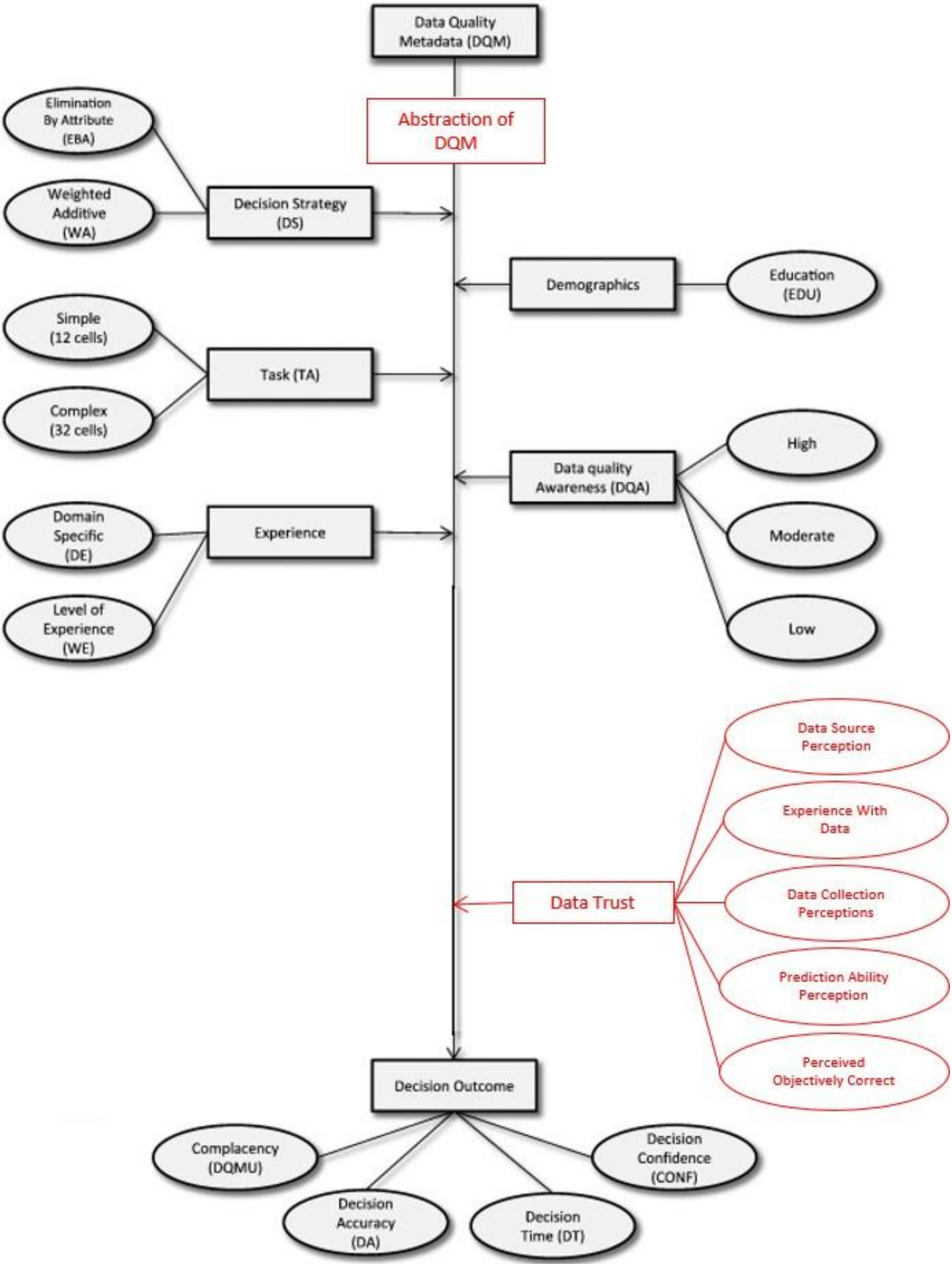


Figure 7.1 Updated Model Of Data Quality Metadata Role In Decision Making

7.3 Limitations

After considering the findings and contributions of this research it's important to appreciate the limitations of the studies. In terms of characterising the decision settings used, both were synchronous team decision making scenarios, a mixture of collocated and distributed, and under medium to long term or low time pressures.

The abstraction of the data quality metadata, using the traffic light system to indicate high to low quality data, presents a potential barrier to colourblind users.

There will be challenges in transferring findings and observations from campuses up to cities. The differences in dimension and structure aren't trivial. Some campuses are small cities, and can act as testbeds, but their scale and operation benefit them in some ways that cities struggle. Campuses are mostly run by a sole owner of the buildings and infrastructure, and are favourable for implementation and acceptability of testing and technologies because of their student and faculty "citizens". They draw private and public partnership well, and are manageable scales for groups such as the PMGs earlier in this thesis to be aware of and account for concurrent and future projects. Cities are more distributed in their operating bodies, ownership and management of services and infrastructure, and the scale of population and consumption. This doesn't mean findings aren't transferable from campus, but there will be obstacles to translating technologies or practices beyond simply upscaling. There is complexity in the widening and diversifying of stakeholders and interests.

The sample sizes, in both the exploratory and experimental study, were relatively small. They were sufficient to reveal patterns in sentiment from the thematic analysis of the interview in study 1, and to see differences in trust and outcomes in the vaccination site study. Further project management groups would have allowed comparison across more than two capital projects, potentially revealing greater variation in the operation and experience of the groups dependent on the project. In the second study, the split of 9 groups across 3 tool versions makes it harder to identify and isolate any interfering factors such as significant strategy game experience or technical literacy. These are mentioned in the discussion of the findings, but additional groups would have helped to confirm the influence of these factors on decision outcomes.

In studying under a serious game framework, to encourage roleplaying of the pandemic response team, it's difficult to understand how much metagaming was going on and the influence of lived experience of the Covid pandemic. Steps were taken in study design, to use a fictitious location, virus, and vaccines, to restrict influence of real-world experience, but the recency of the Covid pandemic served both as an engaging factor and a risk in the study. The metrics the groups would be scored on weren't shared with groups ahead of the task, but some participants did demonstrate an amoral approach seeking to achieve highest numbers without consideration for population vulnerabilities, calling it a numbers game when trying to reach a decision. In a similar way some groups indicated how they could ignore the months or longer scale considerations of the decisions they faced as they had been tasked with just a one-month response. In the real world, decision makers could have more than an hour available to complete this sort of task, and so the study conditions do limit the ability to generalise all the findings.

In the experimental study, a group chair or leader wasn't set. The role was emergent through the groups, or in some cases distributed across participants, and it is difficult to quantify the impact of this allocation or distribution of a team leader on the performance of the groups. There is a chance that some of the underperforming groups would have benefitted from a clearly allocated team leader to direct the decision process more strictly, and similarly that the overperforming groups may have benefited significantly from their ability to organise themselves efficiently, independent of the tool version they were using. Task freeze was observed most strongly in groups in detailed metadata groups and with no emergent leader the direction of the relationship wasn't clear.

The participants in the experimental study were non experts, mostly students, and their familiarity with the types of data used in the decision support tool can limit the generalisation of the findings. There is a strength in the findings for the potential uses of data quality metadata abstractions with novice and non-expert data users, but this doesn't mean experts will have the same responses to the abstractions. Experts are more likely to have the ability to interpret detailed data quality metadata than the non-experts in this study. It is expected though that the relative differences in measures improved by the abstraction will stay the same, whether the effect is as significant is uncertain. Expertise in a domain doesn't mean expertise in all domains though, decision makers won't necessarily be experts in all the data and areas that they can encounter in decision making. The study participants may also not be as motivated as their real-world counterparts. However, increases in use of machine learning algorithms and analytics in decision support systems could see inexperienced decision makers tackling more tasks that are more complex and are beyond their areas of expertise.

Though clear increases in data trust were observed with the introduction of abstract metadata, there was little difference in the decision outcomes of the abstracted and non-metadata groups. The top performing group may be explained by their significantly higher strategy game experience and tech literacy than the other study groups, but adjusting for these the performances of those two conditions are still similar. It’s suggested in chapter 6 that the study design may have contributed to these similar task performances, that the general quality of the data across the tool was good, and so there were few penalties to groups that didn’t spend as much time considering the quality of the data they were using. Qualitatively, groups in the abstracted metadata condition handled the poor quality data better, more readily noticing and negotiating how to use it in their decision. Groups in the non-metadata condition eagerly accepted some figures that were of low quality because they improved how well it appeared the group was doing, saving significant money in their budget for example. Quantitatively these findings aren’t reinforced. In a similar way, the confidence in the decisions was not significantly different for groups in the non- or abstracted metadata conditions.

The findings clearly show a benefit of abstracted data quality metadata over the detailed version, but limited benefit beyond improved data trust against the non-metadata groups. It’s suggested that these two conditions would move apart in scenarios with more unreliable data, but without that validation it is difficult to be certain of the generalisation of those findings to other settings.

The reporting method of trust scores in the focus groups could be susceptible to anchoring effects that would skew groups scores to the first participant that responded. However, the qualitative discussion around trust in the datasets didn’t highlight a significant disagreement between the trust score and the motivation or justification behind the group scoring.

Generally, it’s expected these findings may translate well to other medium and low time pressure situations, but less so to high pressure scenarios. In these high time pressure decision making scenarios, it is expected that groups and individuals are more likely to default to existing experts or predetermined protocols to handle lower quality data than to spend time negotiating the truth in the ways observed in chapters 3 and 6. In the cases of fast decision making in an emergency, there is less manoeuvrability to negotiate between datasets being used based on uncertainty or trust of individuals in datasets than the other settings.

7.4 Future work

There is good support in the findings of this research for traffic light abstractions of data quality metadata, a contribution of simplified metadata data quality and its effect on trust in data. The abstraction raises questions about the thresholding of those traffic lights, who is responsible for the thresholding, and if and how the approach is generalised. Though few participants questioned the source of the data quality rating in the study, there is a question around the attitudes of data users towards potential data broker or similar bodies that could provide the data. This asks the question of whether, and if so, how much, the data users need to trust the threshold method to be comfortable using the abstraction or to see the effects.

The type of metadata made available to users, more specifically, how the data-quality information is recorded and presented matters. The way the data are presented, such as verbal, numerical, or visual scales, affects decision behaviour. Trying to generalise the abstraction process, data quality could be measured or transformed to a 0 to 1 scale, lending itself to a threshold or traffic light banding approach. Evaluating data into categories such as good, average, and poor also lends to the traffic light abstraction. Each of these presents a challenge with the variety of data types and characteristics to generalise where to draw the lines for categorised data quality. The traffic lights work as intended but how should they be reached reliably? There is an opportunity for one of or a combination of algorithms, machine learning, equations, and judgement calls. More work is needed to understand how each of these could address the thresholding question and the implications for scaling to larger datasets and more varied decision making settings. This is potentially labour intensive and can require broadly expert knowledge, prompting the question of where the responsibility lies. Data users, owners, and brokers each have their own issues of trust, expertise, and interest. Someone acting not maliciously, but without interest in the effect of the thresholding on decision makers, could influence the outcome of a decision.

The above raises a subsequent question of if or when the effort is worth it, and when a generalised tool is sufficient. A focused tool with bespoke data quality metadata abstractions can focus people and discussions. How can people move easily between the more generalised and more bespoke options?

These findings of this research need to be explored in other decision making settings to see in what ways they are replicated and what factors interfere or augment what has been observed. The application to a greater range of time pressured decision settings could identify at what point benefits are no longer seen or are greatest. Similarly, varying the expertise and domain experience of decision makers should elicit the strength of data quality metadata abstractions with different data user groups, while also gauging the strength of factors that influence trust in data.

Likewise, there is now a need to see under what conditions decision makers may benefit from both abstracted and detailed metadata. There are scenarios in which the abstraction lowers the barrier to usability in decision making, but that could be enhanced with the option, most likely in lower time pressures, to explore the dataset and associated metadata in more detail. The abstraction levels of metadata needn't be mutually exclusive, they could reinforce each other but further work is needed to understand how this is achieved and the effects of factors such as time available and experience on this.

One of the observations of this research was the apparent independence of decision confidence from the trust in data used in the decision process. There is an opportunity with further research to understand why this behaviour was observed, and under what conditions the decision outcomes, sentiment towards decision outcomes, and sentiments during the process are not proportional to each other. It would have been expected that a greater degree of uncertainty in the data being used would have restricted or reduced the confidence groups had in their proposal. A suggestion is that in this scenario, the time pressure and sense of ability to complete the task sufficiently well had a greater influence on the confidence of groups than the uncertainty in the data. There is an opportunity therefore to look for the time pressure conditions under which the influences on decision confidence change. Under less restrictive time constraints, the groups may have felt more able to complete the task closer to a perceived optimal level and therefore see time not as the limiting factor but others such as the data they were using.

Discussed earlier in this chapter, it's suggested that the lack of difference in decision outcomes between abstracted and non-metadata groups in study 2 is a result of the generally good data quality in the study design. Therefore, this study should be repeated with a greater range of data quality to reveal how this impacts the performance of the abstracted metadata over detailed or non-metadata groups. It's expected that in a scenario with greater data quality variance, the abstracted tool version would come into its own, mitigating the risks of low quality data, while non-metadata groups would be penalised in a way they weren't by the study design originally.

It is mentioned in the contributions section of this chapter, but recommendations for future work encourage greater awareness of the whole picture, the decision outcomes in hand with the process and sentiments during it. There is value in a better understanding of the interconnectedness of these factors, and the conditions under which they are amplified or not.

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Appendix A

Exploratory Study Semi-Structured Interview Question Guide

Introduction to participant:

- Who they are and what they do at the university?
- What was their role on the PMG?
- Have they been part of a PMG before?
    - Were they given guidance on how PMGs work before the group was set up?
- Who do they represent?
- What did they do as part of this group on this project?

Summary/framing of the project:

- What was the purpose of the development – the initial problem identified and the solution(s) offered?
- Were there major and sub-goals for this project?
    - If so, what?
- Who were/are expected users of this building?
- Do you think any were left out during the process?
- How were the needs of users accommodated/ensured?
- Were impacts of the building/project on surrounding area considered, for example parking space, people movement and requirements?

Wider PMG working/process:

- How frequently did the PMG meet/have discussions, and at what stages over the project?
    - Did this change over the project?
- Could they give some examples of decisions the PMG had to make during the project?
- To what extent in these discussions/decisions were the whole group involved or handled through subgroups/individuals?

Data use:

- Was there any data shared with and used during PMG discussions?
    - What sort of data, examples?
    - Nature of this data e.g. How spatial was it (codify it such as room to room level, building level, campus, wider institution), was it spatiotemporal or just spatial?
    - How was it presented?
- Was data shared outside of the PMG to stakeholders or for external discussions?
- Was any data generated by/because of this project/group?

Working methods:

- How did they communicate/work as part of the group (e.g. Online, email, in-person meetings group/subgroups)?

- Were any tools used during this project within the group (when identifying/presenting the problem/solution/monitoring progress or post occupancy)?
- Would they describe the process for this PMG as reactive or proactive?
    - Did this change over the stages of the project?

Reflective:

- Were there any unexpected challenges during this project?
    - How was this resolved?
- Would you have wanted access to more or different data (even if its not something currently captured on campus for any of the stages)?
- Is there anything you would have done differently if you went through this project again?
- What lessons did you learn/are you using anything now that you learned?

Appendix B

Experimental Study Pre-Task Participant Questions

Pre task questions (and actions)

Consent forms and study information etc have been sent round ahead of time. Check people in the call, that they've sent consent form and if not any questions before being comfortable signing and sending, need in before starting the study. Any other ethics/consent-related questions before we start?

Start recording

Some background questions – each participant to give self-evaluated rating 1-5 (1 low 5 high) of experience with/measure of: 1) tech literacy 2) GIS (geographic information systems) 3) strategy games?

Note about allowed to use pen or paper or a separate word processor to make some notes on while you work, but any you do make will be requested a copy at the end of the session as part of the study.

You should be able to complete this task using information supplied in the tool/interface that is going to be shared with you and by working together, it doesn't require prior knowledge or experience, if you're unsure first try looking and clicking around the tool and talking with each other, there are some tool tips in there that give more information, clicking most column/data headings will bring a pop up with a little more information (and in detailed meta version some extra information about the datasets). Then if you are still unsure, I will be here on the call but you should manage without me.

Opportunity for any more questions before starting the experiment. You're given around 45 minutes for the task, I'll let you know when we're getting close to the end of the time. After you've finished with the task we'll go through some follow up questions about the exercise and the tool.

By the end of the task you'll need to propose the list of sites that will be used along with some more details, and explain why you've chosen this plan. Table in chat is a suggested format for proposal at the end, makes sense once you open the tool in a minute

Site(s) selected	Staffing Model (n/a or 1 or 2)	Medically Trained Staff Assigned	Volunteer Staff Assigned	PhasTech Doses	BioMax Doses
37	2	15	10	25000	15000
41	1	24	17	54000	34000
43	1	22	19	40000	42000
...	...	...	...	...	...

There is a general task brief and a role specific brief when you load up to have a read of before getting started, you've each got a different role in the team for this scenario. Assign participant numbers and then group study code is shared. Link to the tool in chat and let them begin.

Re stress the pop ups for headers about each data set. And time.

Link to browser-based tool.

Appendix C

Experimental Study Post-Task Focus Group Questions

Each to click participant number and submit button top middle of the screen. This is sending the logs from the tool.

Post task

1. Could you share your proposal of sites to use and distribution of staff and vaccine doses, and briefly justify how you made the decision?

Site(s) selected	Staffing Model (n/a or 1 or 2)	Medically Trained Staff Assigned	Volunteer Staff Assigned	PhasTech Doses	BioMax Doses
37	2	15	10	25000	15000
41	1	24	17	54000	34000
43	1	22	19	40000	42000
...	...	...	...	...	...

2. How did you feel about the time available for the task, was the time period; more than sufficient, just about right, or would you have wanted more (how much)?

3. Justified your decision a bit already, could you give a breakdown of how you approached the task from launching the tool and reading the briefs, through to giving the proposal? And if there's anything that you prioritised in making decisions?

4. What's your confidence in the final decisions made, proposed sites and staff/vaccine distributions (main task reminder). Scale 1-10, individuals answer, 1 being this was as good as guessing without looking at the data and discussing it for this long, 10 being confident that this is the best outcome you could find even with any more time.

5. Follow on question(s) what do you think would increase your confidence in the decision, was there anything in particular that held back/undermines your confidence in the proposal?

6. Individuals had roles, with some individual focus/subtasks, how do you think you did? (Go round individuals, role and subtask)

7. Now going to look at trust in the data you were using. Feel free to flick back through the tool to remind yourself of any in particular. Quick fire round the group for each dataset, Rank 1-10 of how much you trusted them, 1 lowest 10 highest: Population within travel distances, vaccinations per day for model 1 and 2, staff needed, minimum medical staff WHO and Model, Maximum volunteers, preparation costs, operation costs, car parking, nearby bus stops, accessibility. Any of those you'd like to expand on particular trust or mistrust in them and why?

8. How did you find using the tool? Ease of use over the task, desires for something missing, frustrations.

9. Did you make any notes or working on paper or word doc/excel or equivalent on your computer during the task? How and why did you use it. (Will need to send a copy to me please, email doc or pic of any paper)

10. (For abstract metagroup) How did you find using the traffic light system? Did you want to know anything more about where the data quality rating came from, did you trust it?
11. (For detailed metagroup) In the more info pop ups there was data quality metadata as well as a description of the data; source, accuracy and completeness. Did you use this at all for any of the data sets, if so how? What was your understanding of the accuracy and completeness? Did you take notice/use the source information? Did any of those factor into your decisions of sites or of data to use or reject.

Appendix D

Decision Support Tool Participant Study Brief

Study Brief

The area is suffering a virus outbreak, a local Pandemic Response Team has been assembled to put together an initial response for the region. The city of Portbridge, its boroughs and surrounding towns/villages, with a population of just under 300'000, need a plan for the first month.

This will be the first wave of vaccinations, so the budget and supplies are limited at this point. You'll need to do the best you can with what we have access to now. 25 candidate vaccination centres have been identified in the region, your task is to select as many sites as you need and propose a plan for the first month response. You need to try and protect as much of the population you can.

There are currently 2 vaccine options, PhasTech and BioMax, they have different supply levels and characteristics that you'll need to take into account, the Logistics official has information on this. By the end of the task you'll need to propose the list of sites that will be used along with some more details, and explain why you've chosen this plan.

Each of you has a different role with some additional information in your brief, you will also have access to this decision support tool with more information about the sites. You should take some time to read the rest of your briefs now before the task starts. You'll have about 45 minutes before the Head of the Pandemic Response Team needs your proposal.

Click on a site and choose a tab to get started!

Appendix E

Decision Support Tool Participant Role-Specific Briefs

Public Health Role

Your role is the Head of the Public Health team working on the response. You have some information about the virus and its characteristics below. You want to prioritise the most vulnerable groups getting vaccinated as soon as possible, the leading risk factor identified at the moment is age. You also want to minimise the cases in the region in 4 weeks when Phase 2 of vaccinations should start. In this first phase, under 16s are not being vaccinated so their data are not shown here or in the support tool. Case rates seem even currently across the region, no particular hotspots.

If a site has poor accessibility then the portion of the population with requirements will not travel to the site. The following percentages of the population have building accessibility requirements: 16-29 (2%), 30-49 (3%), 50-69 (6%), 70+ (24%).

Virus information

Name: Rutilus

R number: 2.1 (R refers to the "effective reproduction number". The R number signifies the average number of people that one infected person will pass the virus to.)

All rates of risk are relative to the 16 to 29 year age category.	16-29	30-49	50-69	70+
Case rate	Ref	1x	1x	1x
Hospitilisation rate	Ref	2x	4x	8x
Death rate	Ref	7x	45x	240x

Current Portbridge data on Rutilus	Cases	Hospitalisations	Deaths
Portbridge Health Trust (based on reg. health service data)	94	8	2
National Model Projection (based on population size)	246	53	15

Transport Role

Your role is the Head of the Regional Transport team. You have some information on the travel in the region. This includes the bus routes and their capacity, road closures, and transport modality choices in the region. Bus capacities will need to be halved due to social distancing requirements being suggested. You want to minimise the reliance on public transport where possible due to the risks of spreading the virus. As the travel distance increases we would expect residents to change modalities of transport, and also become less likely to make the journey for a vaccination.

Road closure for resurfacing and other works: There will be no access to buildings on the following streets for the next month. Vale Street in East Iverswood and Tower Passage in West Bromfol.

Bus Routes	Serviced areas					Bus type	Capacity	Maximum capacity in a week
Route 1	Stotsandburgh	North Kemppatt	South Kemppatt	Salkin		Single decker	70	33880
Route 2	West Bromfol	East Bromfol	East Iverswood			Single decker	70	33880
Route 3	Bridtowatt	Thamlosburgh				Single decker	70	33880
Route 4	Brookhedge	Royal Rellther	East Iverswood	West Iverswood		Double decker	100	48400
Route 5	Thorpecotes	Thamlosburgh	Royal Rellther	Brookhedge		Double decker	100	48400
Route 6	Brookhedge	St Hosher	Cleverhill	Hamplen	Hytheuckley	Double decker	100	48400

Survey of which mode of transport (% respondents likely to use for journey length similar to that used as "Distance 1" from site)			
Car	Bicycle	Walk	Public Transport
60	3	29	8
Survey of which mode of transport (% respondents likely to use for journey length similar to that used as "Distance 2" from site)			
Car	Bicycle	Walk	Public Transport
66	5	13	16
Data from previous year of modality use captured by Urban Traffic Control Centre (% of journeys made by modality)			
Car	Bicycle	Walk	Public Transport
75	8	10	7

Finance Official Role

Your role is the Head of the Finance team working on the response. You've fed into some of the initial forecasts, including the provisional budget for this first wave response. You want to try and keep this proposal for Phase 1, the first month, within the budget, this includes the cost of site preparation and operation, and the costs of staffing them.

Financial budget - £4 million

Logistics Role

Your role is Head of Logistics. You have some information on the sites and vaccines for two different models of site set-up, this includes: the medically trained staff available in the region, the vaccine storage requirements, the supply of both the vaccines. You want to minimise the use of volunteers because of the delay it might cause to rolling out the first phase, and minimise the wasted vaccines. If the number of volunteers exceeds half of the staffing at a site, then the opening of that site will be delayed by 1 week due to training requirements. Vaccine dose distribution for the next month will be set now for manufacturers to handle delivery, they will then be supplied each day at rate of 1000 per day from PhasTech and 500 per day from BioMax to each site selected.

Number of medically trained professionals that can be made available for vaccination centres in the region (medical staffing budget): 250

Vaccine Requirements	Name	Age Range	Storage	Supply (doses)
Vaccine 1	PhasTech vaccine	16+	Cold chain dependent, initially needs storing at -80°C to -60°C, can be stored in a refrigerator (2-8°C) for up 24 hours.	125000
Vaccine 2	BioMax vaccine	50+	Not cold chain dependent, store only needs a refrigerator (2°C to 8°C). During use it can be stored from 2°C to 25°C.	75000

Appendix F

Experimental Study Participants Scores from Quantitative Pre-Task and Focus Group Questions

Pre-Task Question Scores

		Self-evaluated Score (1-5)		
Group	Participant #	Tech Literacy	Experience with GIS	Strategy Game Experience
1	Participant 1	5	1	2
1	Participant 2	5	1	5
1	Participant 3	5	1	4
1	Participant 4	5	1	4
2	Participant 5	2	1	2
2	Participant 6	3	3	3
2	Participant 7	3	1	4
2	Participant 8	2	4	1
3	Participant 9	2	2	1
3	Participant 10	4	1	5
3	Participant 11	4	1	3
3	Participant 12	4	1	3
4	Participant 13	4	1	3
4	Participant 14	4	2	3
4	Participant 15	4	2	4
4	Participant 16	3	2	4
5	Participant 17	4	1	5
5	Participant 18	4	3	4
5	Participant 19	4	2	3
5	Participant 20	4	2	2
6	Participant 21	4	2	2
6	Participant 22	3	2	1
6	Participant 23	4	3	2
6	Participant 24	3	1	1
7	Participant 25	3	1	5
7	Participant 26	5	1	5
7	Participant 27	5	1	4
7	Participant 28	4	4	3
8	Participant 29	4	3	3
8	Participant 30	4	1	4
8	Participant 31	3	1	2
8	Participant 32	3	1	2
9	Participant 33	4	1	3
9	Participant 34	5	1	3
9	Participant 35	4	2	3
9	Participant 36	3	1	2

Post-Task Focus Group Reponses

		Trust Score For Data Set									
Participant #	Confidence in final decision made	Population Bands	Vaccine Throughput	Staff Needed	Min. Medical Staff	Max. Volunteers	Preparation Cost	Operation Cost	Car Parking	Nearby Bus Stops	Accessibility
Participant 1	8	6	7	8	8	8	5	5	10	4	7
Participant 2	6	7	7	8	8	8	4	4	8	9	8
Participant 3	7	7	5	5	6	6	3	5	10	10	7
Participant 4	8	7	5	8	6	7	4	3	5	5	5
Participant 5	7	7	8	9	9	8	7	7	8	9	8
Participant 6	5	8	9	7	8	8	8	8	9	9	8
Participant 7	6	8	6	7	8	9	6	6	10	8	8
Participant 8	6	10	8	8	7	7	10	10	7	7	7
Participant 9	2	6	6	4	2	2	5	5	7	8	6
Participant 10	4	6	7	5	3	3	9	8	10	10	6
Participant 11	3	8	6	5	4	4	6	6	8	9	6
Participant 12	4	5	8	6	2	2	8	8	10	9	6
Participant 13	6	7	7	9	3	5	6	7	9	9	9
Participant 14	7	6	7	9	6	7	8	5	8	10	9
Participant 15	6	9	6	4	6	4	8	9	8	10	9
Participant 16	7	7	7	8	5	2	6	9	5	10	10
Participant 17	6	7	6	8	7	6	7	7	9	10	8
Participant 18	6	7	5	4	6	6	6	6	10	10	7
Participant 19	6	7	7	7	4	10	6	6	5	6	6
Participant 20	5	5	7	8	7	10	8	8	5	10	5
Participant 21	6	10	5	5	5	5	5	5	5	5	5
Participant 22	3	5	7	7	4	3	5	5	7	5	5
Participant 23	3	9	5	5	9	5	8	10	10	10	8
Participant 24	2	9	7	7	9	9	5	8	10	9	5
Participant 25	6	7	5	9	9	6	8	7	9	10	10
Participant 26	7	7	5	9	9	7	8	5	6	9	10
Participant 27	6	8	5	8	8	8	7	6	9	10	6
Participant 28	6	8	6	6	7	7	6	5	9	10	7
Participant 29	7	10	10	10	10	10	10	10	10	10	10
Participant 30	8	10	10	10	10	10	10	10	10	10	10
Participant 31	2	10	10	10	10	10	10	10	10	10	10
Participant 32	8	10	10	10	10	10	10	10	10	10	10
Participant 33	6	5	4	8	4	7	7	5	9	5	2
Participant 34	6	6	5	9	4	6	6	8	7	7	4
Participant 35	7	8	4	8	5	2	3	5	10	5	4
Participant 36	5	6	4	6	5	4	3	7	9	8	4

Appendix G

Decision Support Tool Click Log Breakdown for All Buttons

	Total clicks for group									
Button Clicked	**1**	**2**	**3**	**4***	**5**	**6**	**7**	**8**	**9**	**Total**
Accessibility Header Counter	1	0	0	0	0	0	0	0	0	1
Briefs Tab Counter	87	44	50	41	55	49	50	54	52	482
Bus Route Header Counter	1	0	0	0	0	0	0	0	1	2
Bus Routes Button Counter	8	2	10	2	4	0	20	7	9	62
Car Parking Header Counter	3	0	0	0	0	0	2	0	0	5
Cost Tab Counter	100	106	92	53	74	36	91	97	59	708
Deselect Counter	7	12	1	4	13	2	13	7	1	60
Operation Tab Counter	106	99	115	84	86	35	76	77	96	774
Population Tab Counter	135	117	137	70	89	50	109	92	91	890
Role Brief Counter	64	14	22	37	22	23	35	19	18	254
Site 1 Counter	54	11	11	11	32	16	21	10	17	183
Site 2 Counter	22	9	7	16	26	14	8	18	17	137
Site 3 Counter	13	19	9	28	11	12	19	6	11	128
Site 4 Counter	10	2	20	32	13	21	12	12	15	137
Site 5 Counter	17	4	30	17	10	8	18	6	15	125
Site 6 Counter	19	0	7	27	6	14	10	20	11	114
Site 7 Counter	29	9	11	17	10	12	17	17	11	133
Site 8 Counter	11	0	13	17	7	14	12	12	11	97
Site 9 Counter	29	0	36	24	8	14	15	18	11	155
Site 10 Counter	12	6	11	21	5	16	17	10	9	107
Site 11 Counter	11	21	7	16	14	18	27	6	8	128
Site 12 Counter	10	11	9	22	6	16	11	10	11	106
Site 13 Counter	10	7	21	13	13	12	15	18	15	124
Site 14 Counter	15	8	26	15	17	12	19	12	27	151
Site 15 Counter	13	5	23	18	5	18	21	15	17	135
Site 16 Counter	2	5	13	14	9	19	4	18	13	97
Site 17 Counter	5	2	19	13	5	14	13	6	15	92
Site 18 Counter	16	6	24	11	14	10	13	9	21	124
Site 19 Counter	8	1	9	10	17	20	9	12	18	104
Site 20 Counter	28	0	17	10	10	11	5	25	8	114
Site 21 Counter	32	6	39	23	12	21	19	28	33	213
Site 22 Counter	35	0	43	13	17	18	16	21	23	186
Site 23 Counter	29	4	21	14	12	24	25	8	11	148
Site 24 Counter	26	5	11	18	8	14	9	16	15	122
Site 25 Counter	28	4	11	28	9	18	15	23	14	150
Site Op Mod 1 Header Counter	16	6	2	0	0	4	0	11	0	39
Site Op Mod 2 Header Counter	14	3	1	0	0	2	1	12	0	33
Site Prep Bio Header Counter	0	0	1	0	0	4	0	0	1	6
Site Prep Both Header Counter	0	0	1	0	0	1	0	0	1	3
Site Prep Phas Header Counter	0	0	1	0	0	4	1	0	0	6
Study Brief Counter	10	9	18	10	17	13	10	10	6	103
Throughput 1 Header Counter	1	0	3	0	3	5	0	3	3	18
Throughput 2 Header Counter	0	0	0	0	1	6	0	3	1	11
Total Max Vol 1 Header Counter	1	0	0	0	0	1	0	0	0	2
Total Max Vol 2 Header Counter	0	0	0	0	1	0	0	0	0	1
Total Min Med Pod 1 Header Counter	1	0	0	0	2	0	1	0	1	5
Total Min Med Pod 2 Header Counter	0	1	1	0	1	2	0	2	0	7
Total Min Med Who 1 Header Counter	2	0	0	0	1	1	1	0	1	6
Total Min Med Who 2 Header Counter	0	0	1	0	1	2	0	2	0	6
Total Staff Mod 1 Header Counter	2	0	0	0	0	0	1	1	0	4
Total Staff Mod 2 Header Counter	0	0	0	0	1	0	0	1	0	2
Transport Tab Counter	59	50	37	43	60	40	53	62	60	464
Travel Distance 1 Counter	57	13	60	17	25	14	90	45	55	376
Travel Distance 1 Header Counter	1	0	1	0	0	0	0	1	0	3
Travel Distance 2 Counter	57	15	60	23	23	19	95	48	80	420
Travel Distance 2 Header Counter	1	0	0	0	0	0	1	2	1	5

*a team member exited tool and reset during study

Appendix H

Exploratory Study Ethics Forms

PROJECT INFORMATION

University of Nottingham
UK | CHINA | MALAYSIA

Date: 03/02/20

Project: Exploring data use in sense making and decision processes for campus and city development projects

School of Computer Science Ethics Reference: CS-2019-R29

Funded by: Horizon Centre for Doctoral Training at the University of Nottingham (UKRI Grant No. EP/L015463/1) and by Ordnance Survey

Purpose of the research. This study aims to understand the structure of the sense making and decision process for significant development projects on campuses (as defined by University of Nottingham Estates on a combination of budget, problem complexity, range of stakeholders involved, and expected impact of the work and project), and also to understand the extent to which data is currently used in these processes. This forms a part of a larger project to understand how the decision making and sense making in the context of campuses and cities can be supported with data/technology to enable the understanding of and interaction with the Smart Campus and Smart City. This study hopes to elicit a taxonomy of decision making by stakeholders in large scale campus projects to identify opportunities in the process to introduce data/more data generated on/by the campus and its users.

Nature of participation. Participation in this study is entirely voluntary.

Participant engagement. This study involves a series of interviews being conducted with individuals involved in development projects on the University of Nottingham campuses. Taking part in the research requires the participant to take part in an interview which will be recorded for transcription.

Benefits and risks of the research. It is anticipated this research will improve the understanding of the sense making and decision making process for large development projects at the University of Nottingham, particularly where multiple stakeholders are involved. Your participation may help us to identify opportunities for greater visualisation and use of data in the process to improve understanding of stakeholders from problem identification through to project completion and evaluation, therefore working to enable a smarter campus. Interviews will be pseudonymised so there should not be a risk of identification from any transcript excerpts in reporting or publication of findings.

Use of your data. The transcriptions of the interview recordings will be used in supervision meetings and with the industry partner to discuss opportunities for the next stage of research in the PhD, and also be subject to thematic analysis to develop a framework of sense making and decision making by groups of multiple stakeholders on the university campuses. The findings will be published as part of a thesis and potentially presented at conferences, at this point individuals will not be identifiable from data presented.

Future use of your data. The recordings of interviews will be transcribed, after which transcriptions will be stored securely in a University of Nottingham SharePoint folder where it will remain for the period of the research. The University may store your data for up to 25 years and for a period of no less than 10 years after the research project finishes.

Procedure for withdrawal from the research. You may withdraw from the study at any time and do not have to give reasons for why you no longer want to take part. If you wish to withdraw please contact the researcher who gathered the data. If you receive no response from the researcher please contact the School of Computer Science's Ethics Committee.

Contact details of the ethics committee. If you wish to file a complaint or exercise your rights you can contact the Ethics Committee at the following address: cs-ethicsadmin@cs.nott.ac.uk

CONSENT FORM

Date: 03/02/20

Project: Exploring data use in sense making and decision processes for campus and city development projects

School of Computer Science Ethics Reference: CS-2019-R29

Funded by: Horizon Centre for Doctoral Training at the University of Nottingham (UKRI Grant No. EP/L015463/1) and by Ordnance Survey

Please delete as appropriate

1. Taking part in the study

a) I have read and understood the project information sheet dated 03/02/20 or it has been read to me. I have been able to ask questions about the study and my questions have been answered satisfactorily.	**Yes**	**No**
b) I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	**Yes**	**No**
c) I understand that taking part in the study requires me to provide data and that this will involve taking part in an interview.	**Yes**	**No**

2. Use of my data in the study

a) I understand that data which can identify me will not be shared beyond the project team.	**Yes**	**No**
b) I agree that the data provided by me may be used for the following purposes:		
– Presentation and discussion of the project and its results in research activities (e.g., in supervision sessions, project meetings, conferences).	**Yes**	**No**
– Publications and reports describing the project and its results.	**Yes**	**No**
– Dissemination of the project and its results, including publication of data on web pages and databases.	**Yes**	**No**
c) I give permission for my words to be quoted for the purposes described above.	**Yes**	**No**

Please tick the appropriate boxes **Yes** **No**

3. Reuse of my data

a) I give permission for the data that I provide to be reused for the sole purposes of future research and learning.	**Yes**	**No**

b) I understand and agree that this may involve depositing my data in a data repository, which may be accessed by other researchers **Yes** **No**

4. Security of my data

a) I understand that safeguards will be put in place to protect my identity and my data during the research, and if my data is kept for future use. **Yes** **No**

b) I confirm that a written copy of these safeguards has been given to me in the University's privacy notice, and that they have been described to me and are acceptable to me. **Yes** **No**

c) I understand that no computer system is completely secure and that there is a risk that a third party could obtain a copy of my data. **Yes** **No**

5. Copyright

a) I give permission for data gathered during this project to be used, copied, excerpted, annotated, displayed and distributed for the purposes to which I have consented. **Yes** **No**

b) I wish to be publicly identified as the creator of the following works: audio recordings and their transcripts. **Yes** **No**

6. Signatures (sign as appropriate)

<u>Digital signatures accepted due to Government measures in place impacting in-person research</u>

Name of participant (IN CAPITALS)	Signature	Date
Name of researcher (IN CAPITALS)	Signature	Date

7. Researcher's contact details

Name: Peter Boyes

Phone: 07964192051

Email: Peter.Boyes@nottingham.ac.uk

Appendix I

Experimental Study Ethics Forms

PROJECT INFORMATION

University of Nottingham
UK | CHINA | MALAYSIA

Date: 10/01/22

Project: Exploring the sensemaking and decision processes for vaccination centre locations

School of Computer Science Ethics Reference: - CS-2021-R20

Funded by: Horizon Centre for Doctoral Training at the University of Nottingham (UKRI Grant No. EP/L015463/1) and by Ordnance Survey

Purpose of the research. This study aims to understand the structure of the sensemaking and decision process for vaccination centre sites ahead of a vaccine roll-out in a fictional city during a pandemic. In particular the study aims to understand the impacts of a technology intervention on group interactions and decision outcomes using a bespoke spatial decision tool. The findings from this study will inform part of a larger project to understand how the decision making and sense making in the context of campuses and cities can be supported with information technology.

Nature of participation. Participation in this study is entirely voluntary.

Participant engagement. This study involves an exercise being conducted with groups roleplaying as the decision making team for a fictional city and their choice of vaccination centre during a pandemic in their region. The study will follow a workshop format composed of the following stages: a pre-task brief to introduce decision support tool and individual roles, a roleplaying task, a post-task debrief and focus group on the team members' experience of the task.

No prior expertise or preparation is needed to take part in the study. All necessary instructions and information will be provided in the briefing document. The task is a series of decisions for your team to make between a set of candidate vaccination sites your team will be provided with. Sites will have associated information such as costs to operate, potential vaccination rate, and population covered within certain travel distances.

Taking part in the research requires you to take part in a Microsoft Teams call for approximately 1.5 hours which will be recorded, along with system logs from the decision tool, and copies requested of any notes taken during the task. This Microsoft Teams meeting will be hosted through a UoN Teams account, and will be the account used to record/collect data

Benefits and risks of the research. It is anticipated this research will improve the understanding of the team sensemaking and decision making process for multidisciplinary medium-time pressured projects. Your participation may help us to identify opportunities for greater visualisation and use of decision support systems in the process to improve understanding of stakeholders from problem identification through to project completion and evaluation. Workshops will be pseudonymised so there should not be a risk of identification from any transcript excerpts in reporting or publication of findings. The research will gather “mixed” personal data, i.e., data that simultaneously involves multiple participants and/or is irreducibly social in nature. In this case, mixed personal data includes multi-party conversation and interaction recorded on video, audio, and text (MS Teams meeting functions). We can only delete mixed personal data if all parties included in it withdraw their consent, however, we will redact any data that identifies you in public presentations and reports of this research insofar as this is practicable.

Use of your data. Data in this case refers to personal data that is to be collected during the study period (pre-task briefing, group task, and post-task debrief and focus group exercise all to be conducted in a single Teams call) and includes:

1. Video/Audio/Text recordings of the workshop, collected through the built-in meeting record function of Microsoft Teams (video of call participant cameras, audio from participants, and text from the meeting chat that may be used).
2. In the pre-task briefing, participants will also be provided with the data tool, their individual briefing document related to their assigned team role, and asked a few questions to capture levels of experience with strategy games, experience with GIS, and a self-evaluated tech literacy. The post-task focus groups will gather participant insight around their experience of the task such as trust in different city datasets used, conflicts in data sets, confidence in decisions and site proposal made.
3. The tool deployed for use in the task, a decision support system prototype, will capture its system logs to understand how the tool was used during the exercise by each participant.
4. Any note-taking artefacts will be requested from participants, such as paper notes or word processor/ equivalent used by individuals during the group exercise.

This data may be used in supervision meetings and with the industry partner to discuss recommendations for the next stage of research in the PhD. The findings will be published as part of a thesis and potentially presented at conferences, at this point individuals will not be identifiable from data presented.

Future use of your data. The term data is being used as above. Data will be stored securely in a University of Nottingham-provided Microsoft Teams folder where it will remain for the period of the research. The University may store your data for up to 25 years and for a period of no less than 10 years after the research project finishes.

Procedure for withdrawal from the research. You may withdraw from the study at any time up to May 1st 2022, after which point it will no longer be feasible to remove the data from the report and do not have to give reasons for why you no longer want to take part. If you wish to withdraw please contact the researcher who gathered the data. If you receive no response from the researcher please contact the School of Computer Science’s Ethics Committee.

Contact details of the ethics committee. If you wish to file a complaint or exercise your rights you can contact the Ethics Committee at the following address: cs-ethicsadmin@cs.nott.ac.uk

CONSENT FORM

University of Nottingham
UK | CHINA | MALAYSIA

Date: 10/01/22

Project: Exploring the sensemaking and decision processes for vaccination centre locations

School of Computer Science Ethics Reference: - CS-2021-R20

Funded by: Horizon Centre for Doctoral Training at the University of Nottingham (UKRI Grant No. EP/L015463/1) and by Ordnance Survey

Throughout this form the term data is used several times, in these cases the word refers to personal data that is to be collected during the study period (pre-task briefing, group task, and post-task debrief and focus group exercise all to be conducted in a single Teams call) and includes:

5. Video/Audio/Text recordings of the workshop, collected through the built-in meeting record function of Microsoft Teams (video of call participant cameras, audio from participants, and text from the meeting chat that may be used).
6. In the pre-task briefing, you will be provided with the data tool, and be asked a few questions to capture your level of experience with strategy games, experience with GIS, and a self-evaluated tech literacy. The post-task focus groups will gather your insight around the experience of the task such as trust in different datasets used, conflicts in data sets, confidence in decisions and proposal made.
7. The tool deployed for use in the task, a decision support system prototype, will capture its logs to understand how the tool was used during the exercise by each participant.
8. Any note-taking artefacts will be requested from you, such as paper notes or word processor/ equivalent used during the group exercise.

Please delete as appropriate

1. Taking part in the study

a) I have read and understood the project information sheet dated 10/01/22 or it has been read to me. I have been able to ask questions about the study and my questions have been answered satisfactorily. **Yes** **No**

b) I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study up to 15th May 2022 , without having to give a reason. If I withdraw, I understand that my individual data will be deleted, but that my data including other people will not be deleted. **Yes** **No**

c) I understand that taking part in the study requires me to provide data and that this will involve taking part in a group task, and post-task debrief. **Yes** **No**

2. Use of my data in the study

a) I understand that data which can identify me will not be shared beyond the project team. **Yes** **No**

b) I agree that the data provided by me may be used for the following purposes:

– Presentation and discussion of the project and its results in research activities (e.g., in supervision sessions, project meetings, conferences). **Yes** **No**

– Publications and reports describing the project and its results. **Yes** **No**

– Dissemination of the project and its results, including publication of data on web pages and databases. **Yes** **No**

c) I give permission for my words to be quoted for the purposes described above. **Yes** **No**

3. Reuse of my data

a) I give permission for the data that I provide to be reused for the sole purposes of future research and learning. **Yes** **No**

b) I understand and agree that this may involve depositing my data in a data repository, which may be accessed by other researchers **Yes** **No**

4. Security of my data

a) I understand that safeguards will be put in place to protect my identity and my data during the research, and if my data is kept for future use. **Yes** **No**

b) I confirm that a written copy of these safeguards has been given to me in the University's privacy notice, and that they have been described to me and are acceptable to me. **Yes** **No**

c) I understand that no computer system is completely secure and that there is a risk that a third party could obtain a copy of my data. **Yes** **No**

6. Signatures (sign as appropriate)

Digital signatures accepted due to Government measures in place impacting in-person research

Name of participant (IN CAPITALS)	Signature	Date

Name of researcher (IN CAPITALS)	Signature	Date

7. Researcher's contact details

Name: Peter Boyes

Phone: 07964192051

Email: Peter.Boyes@nottingham.ac.uk