Designing Data Science Software for Social Care Organisations

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ABSTRACT

Within the last few decades, data science has risen towards the top of agendas in public services such as adult social care. Concomitant with this ever-increasing appetite for data science is an expanding catalogue of challenges associated with developing, deploying, and maintaining data science software: choosing the appropriate, if any, analytical technique to use; balancing competing conceptions of success; and sustaining user adoption. In my thesis, I argue that these are *sociotechnical challenges*: issues that arise in the tension between what people do, and how data science software supports, limits, and, crucially, changes what they do. Through design science research, this thesis will develop, demonstrate, and evaluate a design approach for data science software that attempts to address such sociotechnical challenges. The empirical sites in which these research activities will take place are live data science projects with local government organisations responsible for adult social care services in England. The resultant approach will include a conceptual model for sociotechnical data science, process guidance and methods for applying the design approach, and results from applying the approach in a real-world data science project in collaboration with an industry partner.

CCS CONCEPTS

• **Human-centered computing** → *Collaborative and social computing design and evaluation methods*; • **Software and its engineering** → **Requirements analysis**.

KEYWORDS

data science, sociotechnical challenges, social care, design science research

ACM Reference Format:
Tyler John Reinmund. 2023. Designing Data Science Software for Social Care Organisations. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23), April 23–28, 2023, Hamburg, Germany.* ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3544549.3577062

1 INTRODUCTION

Adult social care serves a crucial role in the lives of an estimated 10 million people in England [72]. Adults with a physical disability, learning disability, or physical and mental illness receive assistance with essential daily activities such as eating, washing, and socialising [14]. This care is provided by a 2.5 million workforce and a largely under-recognised foundation of 5.4 million friends, family members, and neighbours [14, 96]. All told, the total value of care provided in the year 2019-20 was estimated to be over £120 billion; this figure includes care that is paid for with public funds by local authorities, privately by individuals, but, mostly, care that is provided informally and therefore left unpaid [14]. Despite its scale and centrality to the lives of many, the adult social care system suffers from sustained under-investment and struggles to meet demand amid decreases in public funding and rising care costs [10, 14, 87] – spurring some commentators to pronounce that England is faced with a "crisis of social care" [23].

In response to these challenges, policy directives and industry initiatives have forwarded data science[1] as a viable solution [27, 71, 73]. So far, data science has been applied across several aspects of adult social care, both within England and internationally. For example, there are ongoing initiatives to integrate care home datasets [9, 36], analyse and predict patterns of demand to inform service provisioning [94, 102], develop data visualisation dashboards [20], and create recommender systems to support care preference surveys [31].

Concomitant with this ever-increasing appetite for data science is an expanding catalogue of challenges associated with developing, deploying, and maintaining data science software in varied sectors. These issues are not merely matters of technical limitations, nor are they solely due to incompetence or lapses in professional judgement. They are, as this body of work proposes, fundamentally *sociotechnical* – they emerge through the mutual constitution of technology and practice [84].

One common challenge is the misapplication of data science. This issue manifests in two ways: one practical, the other ideological. The first takes the form of what the statistician David Hand describes as "errors of the third kind (giving the right answer to the wrong question)" [35]. Questions posed in an organisational context do not neatly map to those which data science can solve; instead, they must be translated to analytically amenable formulations [74, 75]. Yet, for many social decisions, there may be discrepancies between what can be represented in data and the desired organisational objective. For example, a study by Kawakami et al. [46]

[1] In the remainder of this paper, the term data science software is used to refer to software-based systems that support the creation, collation, analysis, and dissemination of large and heterogeneous data sets [21, 49]. While other scholars use terms such as *data analytics*, *business analytics*, *machine learning*, or *artificial intelligence* to refer to similar types of software, the term *data science* expands the focus of attention beyond exclusively analysis of data or software with predictive machine learning capabilities. Data science is more than analysis, comprising activities, such as data generation, transformation, representation, and the people and resources required [21]; and this analysis entails forms other than prediction, such as the use of inferential statistics to identify patterns in data and visualisation to depict these patterns in a communicable form.

CHI EA '23, April 23–28, 2023, Hamburg, Germany

ACM ISBN 978-1-4503-9422-2/23/04.
https://doi.org/10.1145/3544549.3577062

suggests that social workers at a child welfare agency may use a notion of "risk" that fundamentally differs from that which has been operationalised in an algorithmic decision support tool. Meanwhile, the misapplication of data science's ideological manifestation stems from the assumption that any question can be addressed through the use of data science and machine learning [89], such as whether a defendant is ready to be released from prison [2] or which employees are the most productive [41]. Evgeny Morozov's influential concept of "technological solutionism" captures the essence of this perspective. In his writing, Morozov articulates how the presence of vast amounts of data, complex algorithms, and efficient computational storage and processing capabilities afford a tendency in modern society to reframe ambiguous, contested, and intractable social phenomena as defined, certain, and computable problems [66]. A detailed understanding of the problem at hand is a precondition for both answering the *right question* and answering the *question right*.

As this example hints at, data science makes use of and is in fact dependent on access to quality data. Of course, the presence of data is moot if one does not know what to do with these resources. There is a need for personnel with skills in data processing, analytics, and visualisation [25, 91] who can collaborate with various stakeholders, each of whom possess their own diverse skill sets [48, 70, 105]. This multidisciplinary collaboration leads to numerous challenges related to communication and coordination. Most relevant to this research is the issue of competing conceptions of success. In an ethnographic study, Passi and Sengers [75] report on the divergent evaluations of a chatbot between business and data science actors; put simply, business stakeholders evaluate the chatbot in terms of its "practical efficacy" whereas the data science team was concerned with its "algorithmic efficacy." Their finding highlights the difficulty, noted elsewhere, in relating measures of algorithmic performance to broader organisational objectives [54].

Finally, once data science software is deployed in an organisational environment, issues with user adoption persist. Research in domains such as health care and social welfare suggest that adoption is influenced by whether the software addresses a relevant problem for practitioners [26], includes interfaces that enable users to provide real-time feedback [11, 46], and aligns with work practices and environmental constraints [103]. For example, Wang et al. [100] describe the incompatibility between the workflow prescribed by a clinical decision support system and the workplace demands of a health clinic in rural China. To meet the needs of a high number of patients, clinicians adopt workarounds, such as cursory data input, that resultantly deteriorate the system's performance. As this discussion illustrates, designing data science software runs into a series of **sociotechnical challenges**: issues that arise in the tension between what people do, and how data science software supports, limits, and, crucially, changes what they do [1, 80].

2 RELATED WORK

This thesis draws together and will contribute to multiple bodies of literature: *data science design practices*; *human-AI collaboration*; *sociotechnical software design*; and *fairness, accountability, and transparency in machine learning* (FAccT ML). In this section, I provide a brief summary of each area and introduce the gaps which this thesis aims to address.

Data Science Design Practices. As data science has become increasingly common within businesses, governments, non-profits, and research institutions, scholars in HCI and CSCW have taken an interest in the practical activity of doing data science. This growing body of literature explores what it is that data scientists actually do, their modes of collaboration, and the assorted tools these practitioners need to get their work done. These studies point to the discretionary, collaborative, and technologically-mediated human labour required to do data science [50, 68, 75, 101]. Data science teams are made up of variously esteemed experts [68, 81, 95] with heterogeneous skill sets [48, 58, 82]. These practitioners collaborate with both one another as well as with counterparts beyond their organisational boundaries [51, 77].

Within this literature, there are opportunities for further empirical and theoretical contributions. Most studies are restricted to point-in-time interviews with practitioners at large, multinational corporations [e.g., 67, 68, 77, 101]; as such, they remain silent on how work practices, collaboration strategies, and perceptions change over time and differ within vastly different organisational contexts. And in regards to theoretical contributions, there is relatively little direct engagement with established theoretical frameworks from the social sciences; most studies instead adopt a Grounded Theory method [e.g., 51, 68, 74, 75]. The reason why this preference for inductive knowledge generation is notable is that social science scholarship in domains such as interdisciplinarity engage with several issues that have emerged, as well as those which remain absent, from the studies on data science design practices: disparities in social power, epistemological commitments, language, and culture [12, 86]. Therefore, what is missing in this literature is engagement with these theoretical concepts to help explain their relationship to design decisions.

Human-AI Collaboration. A growing body of empirical work explores how situated work practices shape and are shaped by the use of data science, and in particular machine learning-enabled, software [44, 100]. These studies characterise the appropriation of data science software as a productive process that re-configures power relationships and precipitates new forms of work and expertise [41, 42, 45, 53]. Importantly, this influence is not deterministic; it instead emerges through an interaction between behavioural, organisational, and technical factors. For example, Saxena et al. [85] propose the "Framework for Algorithmic Decision-Making Adapted for the Public Sector" to study the role of data science software in child protective services. The ADMAP framework emphasises the role of three dimensions in shaping caseworkers' use of an algorithmic tool: human discretion, including professional expertise, value judgements, and heuristic decision-making; bureaucratic processes, such as organisational resources and constraints, administrative processes and protocols, and laws and policies; and algorithmic decision making, such as relevant data, types of decision-support, and degree of uncertainty around the final decision.

This thesis aims to extend research on human-AI collaboration in two empirical directions. First, few, if any, studies focus on adult social care; this leaves context specific considerations – from the types of services provided to the conditions of the service users –

largely unexplored. Second, few studies investigate the use of data science software over an extended period of time to understand how work practices, organisational structures, attitudes, and skill sets may change [cf. 53, 90]. Therefore, echoing the claims of numerous authors, there is a need for studies in realistic settings that holistically evaluate the use of data science software, taking into consideration the role of organisational, cultural, professional, and temporal dimensions [cf. 45, 57].

Sociotechnical Software Design. In the final decades of the 20th century, several design-related disciplines began to adopt increasingly social sensitivities as scholars and practitioners grew critical of the assumptions, frameworks, and methods underpinning their respective fields [5, 40]. As a result, researchers devised and applied a number of "sociotechnical" approaches to design that draw heavily on the principles and practices of the social sciences to account for the flexibility, nuance, and instability of social settings [1, 43].

Broadly, these fall into three partially overlapping categories. *Intentional* design approaches – for example, goal-oriented requirements engineering [17, 104] and hierarchical task analysis [3, 93] – ask why users do what they do; design is then oriented towards these objectives. Next, *participatory* approaches place users and designers in shared spaces to co-create technology. Within this theme are the Scandinavian [47] and British [69] traditions of participatory design, the contemporary field of co-design [83], and the well-regarded value sensitive design framework [29]. Finally, *in situ* design approaches, such as ethnography for design [15] and activity-centred design [32], go directly to the settings of users to understand how they make sense of their everyday experience through their own practical action.

Running across these varied approaches are similar issues which this thesis aims to address. First, these approaches were created in the context of traditional software engineering; therefore, most have not yet been adapted to contemporary data science design considerations. And despite the abundance of methods, there remains limited adoption in industry [28, 60]. Some researchers attribute this research-practice gap to their complexity [65] and the dependence on their progenitors [24]. Finally, there is little research that systematically evaluates the effect of adopting sociotechnical approaches on the outcomes of design [6, 28, 39].

FAccT ML. Within the last few years, an interdisciplinary group of scholars have made substantial contributions to the nascent field of FAccT ML. There has been a rush of work to develop tools and processes that mitigate concerns of algorithmic bias [13, 56, 59], devise algorithmic auditing frameworks [8, 78], and improve data set and model documentation practices [33, 61, 63]. Accordingly, researchers have grown interested in the use of these sociotechnical interventions. For example, studies note a disconnect between the solutions offered by researchers and the needs of practitioners [38, 97], explore how organisational circumstances shape their adoption and use – emphasising the importance of building sociotechnical interventions on existing organisational practices [79, 92] – and evaluate practitioners' experiences employing them [7, 19, 55].

There are opportunities to extend this literature both theoretically and empirically. First, most studies intervene in the design process at a stage once the problem and its corresponding solution have already been defined. In the words of Sanders and Stappers [83], these interventions pass over the "fuzzy front end" of design in which the "deliverable of the design process" is not known. For example, questions tend to focus on how to make a particular type of system fairer, responsible, or more transparent – for example, credit risk scoring [59], population management in a refugee camp [18], or risk assessments for child welfare [13]. This starting point assumes that a well-defined and agreed-upon problem exists; the focus therefore goes towards *how* to design rather than *what* or, more radically, *whether* to design [4]. Yet, in many complex social settings, this is far from the case: problems are ambiguous and contested [74], and technological interventions are not always appropriate [34, 89]. And as with the sociotechnical approaches to software design, the question of evaluation persists. Few studies evaluate how practitioners use these interventions collaboratively and within their day-to-day work [19]. Additionally, when evaluations are conducted, they exclusively focus on practitioners' experiences with the intervention [7, 19, 55]. As such, there is a need for studies which evaluate how sociotechnical interventions affect organisational practices, software design, and, ultimately, the stakeholders implicated by the technology's use.

3 RESEARCH AIM AND QUESTIONS

The aim of this thesis is *to create a design approach that addresses sociotechnical data science challenges*, explored in the context of England's adult social care sector. A design approach here refers to a set of constructs, conceptual models, process guidance, methods, and instantiations. As part of a postgraduate studentship, this research will be conducted in partnership with a consultancy that provides professional services to local authorities in England that have statutory responsibilities for adult social care services.

In pursuit of this aim and in light of the previously discussed research gaps, this thesis will address the following questions:

RQ1: (a) How do sociotechnical data science problems manifest in adult social care? (b) What are the common characteristics of these problems? (c) How do data science practitioners attempt to resolve these problems?

RQ2: (a) What local practices exist within adult social care that may contribute to an understanding of sociotechnical data science software design? (b) How do data science practitioners incorporate these practices into design activities? (c) How do data science practitioners achieve these activities?

RQ3: (a) How can an approach for sociotechnical data science design be applied in adult social care organisations? (b) What conditions facilitate and challenge its use? (c) How do stakeholders involved in design value the approach? (d) How do stakeholders not directly involved in design value the resultant product?

4 RESEARCH STRATEGY

The questions posed above imply two interrelated research directions: one focused on problems, the other on solutions. The first is *exploratory* and seeks to understand local sociotechnical practices. Meanwhile, the second direction is *interventionist*, aiming to iteratively apply and evaluate a designed solution.

4.1 Design Science Research

A problem-solution relationship is emblematic of design science research [99]. As defined by Hevner and Chatterjee [37]:

> "Design science research is a research paradigm in which a designer answers questions relevant to human problems via the creation of innovative artifacts, thereby contributing new knowledge to the body of scientific evidence. The designed artifacts are both useful and fundamental in understanding that problem."

From its problem-centric orientation and demands for methodological rigour it facilitates the production of knowledge that is both scientific and practically relevant [76]. Peffers et al. [76] propose a design science research methodology which includes the following iterative phases: identify problem and motivate, define objectives of a solution, design and development, demonstration, evaluation, and communication. The work packages (WP) elaborated in the following sections, and represented in Table 1, comprise the design science research approach employed in this thesis.

4.2 Pilot: Exploratory Study on Adult Social Care Operations

Objective. This pilot aims to explore how stakeholders involved in the operation of care services perceive current digital technologies to inform an understanding of sociotechnical data science problems in the sector.

Research design. Given this work package's exploratory aim, a qualitative design was employed. Between December 2021 and April 2022, I interviewed 16 social care practitioners. The participants occupy a variety of roles involved in the operation of care services, such as a care coordinator at a home care provider who manages the schedules of domiciliary care workers, an IT manager at a local authority who maintains the digital care records system, and an occupational therapist involved in developing the local authority's care technology programme. Because of the diversity of roles, I followed an unstructured interview approach [52]; instead of relying on predefined questions, I focused on three topics to cover during the interviews, and posed questions relevant to these topics as they arose in the discussion. The interviews centred around the topics of *current practice*, *desired practice*, and *technology use*.

Outcomes. These interviews led to an exposition of the social care operations journey in terms of both its constituting activities and supporting digital technology. This journey is continuous and non-linear, and brings together a diverse array of practitioners. It is supported by numerous digital technologies that monitor the progression of service users, store and manage information, maintain the schedules of care workers, track care visits, and manage the administration of medication. Across these diverse technologies, participants value system interoperability and feature customisability. These findings contribute to an initial understanding of **RQ1**.

4.3 WP1: Local Data Science Practices

Objective. The aim of this work package is to understand the challenges and practices within adult social care that may contribute to an understanding of sociotechnical data science software design.

Research design. This work package will employ an exploratory sequential design: a qualitative exploration with a smaller sample will contribute to the design of a survey instrument; the instrument will then be distributed to a larger sample [16].

In the first phase, qualitative data will be collected primarily through participant observation with a data science team at a consultancy based in Oxford. As mentioned, most studies on data science practices rely on interviews [e.g., 51, 58, 67, 68, 77, 82]; to complement these point-in-time investigations, participant observation allows for a deep understanding of social interaction in a specific context across time, supports the identification of unusual and unexpected results, and provides access to tacit knowledge [16]. The observational data will be supplemented with data collected through semi-structured interviews; this method allows for clarification and targeted discussion regarding specific topics of interest. Additionally, the use of two data collection methods supports the validity of findings by triangulating data sources to provide justification for observed themes [16]. After analysing data through the qualitative data analysis approach set out by Miles et al. [62], the findings will inform the design of a quantitative survey to test the results with a larger population of data science practitioners who work in social care.

Outcomes. At the time of writing, this work package is in progress; it is anticipated to continue until the end of April 2023. It aims to provide empirical descriptions of sociotechnical data science challenges and practices, utilising England's adult social care sector as its case. These empirical descriptions will provide the conceptual foundation for the design approach. This work package addresses both **RQ1** and **RQ2**.

4.4 WP2: Field Experiment

Objective. The aim of this work package is to develop and evaluate an initial iteration of the design approach.

Research design. This study contains two sequential components. First, the analysis from WP1 will be combined with conceptual knowledge from the literature to elaborate an initial iteration of the approach. And the second component of this study will entail an experimental evaluation, adapted from Moody's [64] model for validating information systems design methods.

Field experiments are one of few methods which researchers can use to study system design methods [30]. Therefore, this study will employ a field experiment to explore how practitioners perceive the design approach and identify areas for improvement [98]. Participants will be sampled purposively from the partner organisation. Given the exploratory and formative objectives of the field experiment, a single group experimental design will be followed: all participants will be subjected to the same single treatment. In the case of this study, the experimental treatment will be the design approach.

During the field experiments, I will first train all participants on the design approach. Participants will then receive a scenario

Table 1: Overview of individual work packages comprising the thesis and contributions to research questions (RQ1 – RQ3). ✓ indicates that a work package contributes to a specific research question; ❍ indicates that it does not.

Work Package	RQ1	RQ2	RQ3
Pilot: Exploratory Study on Adult Social Care Operations	✔	❍	❍
WP1: Local Data Science Practices	✔	✔	❍
WP2: Field Experiment	❍	❍	✔
WP3: Empirical Application and Evaluation	✔	❍	✔

on which they will apply the design approach; the scenario will be informed by WP1. Then, to simulate the collaborative dimension of data science [cf. 19], participants will be divided into groups of four. A relatively small group size aims to stimulate involvement of all participants [52]. Within their respective groups, the participants will be asked to outline how they would address the scenario using the design approach. Finally, to gather feedback as soon as possible and to respect participants' time constraints, participants will be interviewed in their groups.

Outcomes. The findings from this stage will be incorporated into the design approach and will inform the evaluation strategy in WP3. Therefore, it provides an initial instance of addressing **RQ3**.

4.5 WP3: Empirical Application and Evaluation

Objective. The aim of this work package is to apply and evaluate the design approach in a real-world data science project.

Research design. A project will be sampled through discussions with the partner organisation. To plan for the application of the design approach, the project team will first go through a training session similar to that conducted in WP2. Planning will also entail defining an evaluation strategy, drawing from Venable et al. [98] and Bossen et al. [6]. An evaluation strategy refers to the evaluation's objective, criteria, methods, and participants; the findings from WP2 will inform these considerations. Once planning activities are complete, the approach will be applied on the sampled project, and evaluation will occur during both design and following implementation.

Outcomes. As with WP2, the findings from this stage will again be incorporated into the design approach. The evaluation findings will contribute to an understanding of the approach's influence on the data science process, as well as the resultant data science software product. Finally, this work package provides a second iteration for addressing both **RQ1** and **RQ3**.

5 DISSERTATION STATUS AND NEXT STEPS

At this stage, I have completed the pilot study and am currently conducting the observational study of local data science practices (WP1). Concurrently, I am elaborating an initial version of the design approach based on the findings from the pilot as well as the related work stated in Section 2: a conceptual model of sociotechnical data science challenges, process guidance for applying the design approach, and methods to assist with the activities which comprise the approach.

From these two strands of ongoing work, I am engaging with several methodological and theoretical questions:

- Conceptual models are useful artefacts for designers as they allow different participants to negotiate a shared understanding of an environment, make expectations explicit, and disseminate knowledge between different stakeholders. But, they come with certain ontological assumptions – the ability to represent a somewhat stable and coherent world – that appear at odds with many contextual studies of technology that favour a perspective that sees reality as a product of social action. How can these different philosophical commitments be reconciled in this situation? That is, how can the benefits of each perspective be brought to bear on the design of data science software?
- Similarly, a significant finding from sociological studies of technology design and use is that context matters. An understanding of technology cannot be separated from the time, place, and people that create or employ it. How, then, can knowledge in the form of design methods based on empirical studies in specific settings be transferred from one context to the next?
- How do foundational principles of data science software design comply with or contravene social behaviour? This question has two depths to it. At one level, it inquires into the relevance of Ackerman's social-technical gap [1] for data science software, and whether any of the technology's specific features move technical design closer to or further away from "social" requirements. On another level, this question considers the work of Dourish and Button [22] on "technomethodology" to explore whether the foundational principles of design for data science software can be re-imagined to better support the nature of social action. Given that data science software design differs from that of traditional software – for example, a lack of modularity and the presence of feedback loops and data dependencies [88] – exploring the connection between social understanding and these principles may offer novel directions of research.

6 PERSONAL BIOGRAPHY

Tyler Reinmund is a 2nd year doctoral student in the Human Centred Computing research group at the University of Oxford. The expected completion date for his doctoral programme is March 2025.

Tyler is supervised by Marina Jirotka and Lars Kunze. His doctoral research is co-funded by Newton Europe and the Oxford-Singapore Human-Machine Collaboration Programme, supported by a gift from Amazon Web Services.

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Received 9 November 2022; revised 5 January 2023; accepted 15 January 2023