AHRC DESIGN FELLOWS
CHALLENGES OF THE FUTURE

AI & DATA

Joseph Lindley and Paul Coulton

Arts and
Humanities
Research Council

Lancaster
University

Glossary of Terms

Artificial Intelligence (AI) - for the purposes of this report we define it as an umbrella term for a range of algorithm-based technologies that solve complex tasks by carrying out functions that previously required human thinking.

Data - this term is principally used in this report in relation to 'training data' which is the initial set of data used by AI systems through which they learn to base subsequent decisions or predictions. However we acknowledge some types of AI systems additional data is collected throughout the process.

Machine Learning (ML) - is a subset of artificial intelligence. Machine learning algorithms build mathematical models based on sample data in order to make predictions or decisions.

Deep Learning (DL) - is a subset of ML that uses neural networks capable of learning unsupervised from data that is unstructured or unlabeled.

Reinforcement Learning (RL) - after initial training the system continues to refine its decisions/predictions based on new inputs.

Neural Networks - describes algorithms whose topology is inspired by the human brain.

Supervised Learning - Supervised learning is when the training data contains both inputs and an output and the algorithm learns the mapping function between input and output.

Unsupervised Learning - Unsupervised learning when the training data contains inputs no corresponding output.

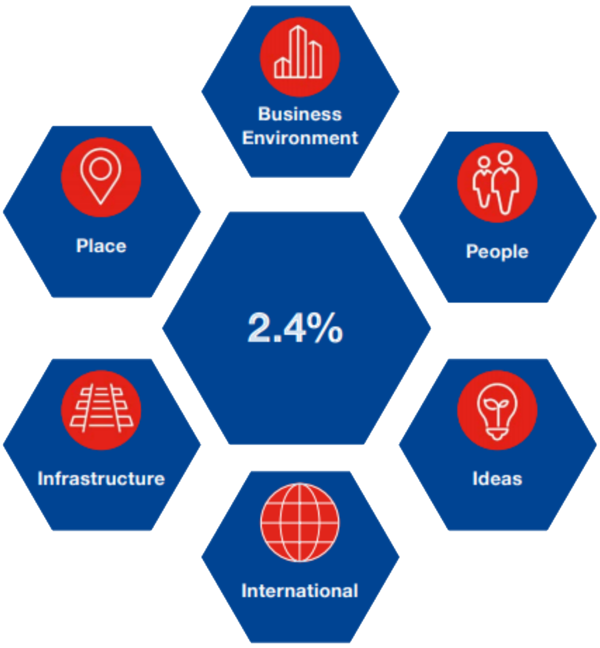
Bias - in this report we are principally concerned with algorithmic bias which describes systematic and repeatable errors in AI Systems that create unfair outcomes, such as privileging one group over others.

1. Introduction

Artificial Intelligence (AI) and Data represent significant challenges of our time. In this report we discuss how Design Research can help address these challenges while growing and supporting the UK's world-leading position in AI and Data innovation.

"Our vision is for the UK to become the best place in the world for businesses developing and deploying AI to start, grow and thrive, and to realise all the benefits the technology offers." [1]

Government projections suggest that AI will add an additional £630 billion to the UK economy within the next 15 years boosting GDP by up to 20%. AI and Data are already an essential component of the national economic engine but the scale of the potential growth is so disruptive it will require a reconfiguration of personal, societal and political relationships with both AI itself (as a class of technology) and Data (as the raw material which enables AI). Increasing research and development spending across the whole economy to 2.4% of Gross Domestic Product by 2027[2] will provide the critical investment necessary to fully benefit from AI and Data, and a key part of this investment is an increase in private sector contribution.



"The UK must seek to actively shape AI's development and utilisation, or risk passively acquiescing to its many likely consequences." [3]

As AI is more widely adopted it will impact all aspects of our life including healthcare (spotting early signs of illness and diagnose disease), governance (to target interventions

[1] https://www.gov.uk/government/publications/growing-the-artificial-intelligence-industry-in-the-uk
[2] https://www.ukri.org/about-us/increasing-investment-in-r-d-to-2-4-of-gdp/
[3] https://publications.parliament.uk/pa/ld201719/ldselect/ldai/100/100.pdf

and identify potential offenders), work (targeting products and services to consumers), and culture (human-machine collaboration). Responding to the gamut of AI's impact will require an equally wide range of disciplinary perspectives across engineering, art, and the humanities. Design Research's ability to work with and among diverse and flexible methods make it a unique toolkit which is apt to respond to the needs of AI's paradigm shift. Design Research can help to optimise the opportunities while simultaneously mitigating the risks that AI and Data pose. Through this report we will:

- Explain why Design Research is relevant to AI and Data innovation.
- Explore how Design Research related to AI and Data is funded.
- Discuss the skills and training requirements of Design Researchers.
- Describe the cutting edge research questions about AI and Data which Design Research can be applied to.
- Plot the landscape of current centres of excellence and partnerships.
- Summarise recommendations, based on the evidence in the report, to enhance University-led Design Research, exploring how partnerships with government and business can create positive economic, cultural, and social outcomes for the whole of the UK.

2. Research Approach

The report is based on original research and qualitative data gathered through interviews with domain experts. In total 16 participants (see profiles in appendix 1) were interviewed. Specific participants were invited to take part in order to represent a spectrum of the Design Research landscape covering various disciplinary alignments, academic and non-academic Design Research practitioners, Design Researchers with historically diverse funding track records, as well as AI and data domain experts with a purview of Design Research.

The semi-structured interviews were conducted according to an interview schedule (see appendix 2) which directly addresses the headings and questions specified for the report while also provisioning for the wide range of perspectives that were participated. Interviewees were asked to consent to be quoted directly without anonymisation, this is an important step in contextualising the breadth of viewpoints upon which the report draws.

The research is conducted from a pragmatic perspective, accepting both that there are multiple, sometimes incompatible, points of view and also that the researchers are in fact part of the research instrument and will inevitably colour how the data is presented and interpreted. Notwithstanding this acknowledgement, the report endeavours to be faithful to the spirit of participants' comments and all participants have had the opportunity to rescind, amend, or add to their quotes as they appear in the report. Where we quote interviewees directly in the report the interviews will be referenced as follows: **"This gets a bit complicated, but you could go back to a kind of Cartesian dichotomy between the physical object and the intelligence" (Auger, 2020)**.

Interviewee	Position(s)	Affiliation
James Auger	Enseignant-chercheur (Lecturer/Researcher)	École normale supérieure Paris-Saclay
Anab Jain	Co-founder and Director	Superflux
Chris Speed*	Programme Director, Design Informatics	The University of Edinburgh
Ewa Luger*	Chancellor's Fellow in Digital Arts and Humanities, Design Informatics	The University of Edinburgh
Bill Gaver*	Co-Director, Interaction Research Studio	Goldsmiths
Andy Boucher*	Co-Director, Interaction Research Studio	Goldsmiths
Ann Light	Professor of Design and Creative Technology	University of Sussex
Alison Powell	Just AI Network (lead) and Assistant Professor in Media and Communications	London School of Economics
Stuart Reeves	Assistant Professor in Computer Science, member of the Mixed Reality Lab and Horizon research institute.	University of Nottingham
Dave Kirk	Professor of Human-Computer Interaction and Director, Openlab	Newcastle University
Ben Kirman	Lecturer, Department of Theatre, Film, Television and Interactive Media and member of Digital Creativity Labs	University of York
Dame Wendy Hall	Co-chair of UK Government AI Review, Skills Champion for AI, Executive Director of Web Science Institute	University of Southampton
Shannon Vallor	Chair in the Ethics of Data and Artificial Intelligence at the Edinburgh Futures Institute	University of Edinburgh
John Vines	Professor, School of Design	Northumbria University.
Julian Bleecker*	Co-founder (Near Future Laboratory)	Near Future Laboratory
Nicolas Nova*	Co-founder (Near Future Laboratory), Associate Professor at the Geneva School of Arts and Design	Near Future Laboratory

Table 1. Interviewees quoted in the report (further profiles included in appendix 1). Those marked with asterisks (*) were interviewed as a pair with their respective colleagues.

3. Viewing AI and Data through a Design Research Lens

3.1 How does AI work?

“If you wish to make an apple pie from scratch, you must first invent the Universe” - Carl Sagan.

Carl Sagan’s enigmatic quip about apple pie is profound because it argues a working knowledge of the *origin* of the Universe is absolutely necessary to have a working knowledge of physics in the real world (or, of an apple pie). Similarly if we are to fully understand the breadth of possibilities for Design Research related to AI and Data it is important to be able to navigate the complexity of landscape to which these terms are applied. It is worth noting while some of this discussion is relevant to the wider arts and humanities in this report we are specifically considering AI and Data through a Design Research lens.

The **“ancient human desire of replicating life” (Auger, 2020)** links together the intrigue of automata such as Vaucanson’s *Canard Digérateur*, Norbert Wiener’s work on *Cybernetics* and later, in collaboration with John von Neumann, the modelling of neurons which led to so-called *neural networks*. In 1956, American computer scientist John McCarthy organised the Dartmouth Workshop, at which the term ‘Artificial Intelligence’ (AI) was first adopted. By this time **“the ability to replicate intelligence starts to become a big obsession with scientists”,** however, **“when we see that applied [today] the reality is much more banale” (Auger 2020)**.

This more banale utilisation of neural networks to process large datasets is part of what we refer to today as AI, but that AI moniker stuck is arguably a matter of luck: at the influential Dartmouth Workshop two key attendees (Allen Newell and Herbert Simon) were minded to refer to the field as *Complex Information Processing* rather than AI. Given how the technology works and how it is used, if we had adopted Complex Information Processing as the field’s label it would, arguably, have led to fewer misunderstandings about what the field actually is, and how it works. Notwithstanding this observation, AI is the term which is widely adopted and hence we must deal with its connotations.

The applications of today’s AI are commonplace, for example spam filters, predictive text messaging, and targeted advertising. However, due to a lack of understanding about what the term AI really represents, and the enduring influence of the field’s grand foundation in the pursuit of artificial life, the perception of AI often transcends its banality. **“It’s quite problematic actually”** notes Anab Jain **“it is sexy to put the term on stuff” (Jain, 2020)**. Some products and services are **“just processing things without any kind of actual learning”** this creates a **“distinction between public perception of AI and actually a computer science perception of AI” (Light, 2020).**

The inescapable link between science fiction and AI fuels the disparity between what people think AI is and what it *actually* is: **“human beings want to make sense of the technology**

and they use old metaphors that came from the sort of science fiction kind of mind-set", moreover, **"AI is a science concept, but it was mostly democratised by science fiction movies or comic books and novels" (Nova, 2020)**. The point is that those democratising and popular visions of AI show machines with a human-level general intelligence (i.e. with the ability to learn how to do different tasks). *The Matrix*, *Blade Runner*, and *2001: A Space Odyssey* - these works of fiction depict 'strong AI' and 'general AI', leaving a residual influence on the public perception of *real* AIs power, for example, facial recognition, natural language processing, and recommendation services. Whilst these everyday systems do 'learn' how to do specific tasks very well indeed, they do not have the general intelligence necessary to reskill themselves, or to spontaneously learn without configuration - as those shown in sci-fi tend to. Notably, among our interviewees, when asked to define AI and to explain the relationship between data and AI, none of the interviewees refer to strong, or general AI as an area currently requiring design research (other than to point out how its vision impacts understanding).

The conceptual space between the entirely fiction (but highly influential) science fiction visions of AI and the very real (but quite mundane) real applications of AI is referred to as AI's *Definitional Dualism* (Lindley et al, 2020). This dualism, demonstrated in Figure 1, can act to stifle progress about the issues to hand because, as Lindley's Law states, "any sufficiently in-depth conversation about 'AI' will result in the dialogue becoming about sentient killer robots[4]". The murkiness and ambiguity arising from AI's Definitional Dualism is also, arguably, what provides the rhetorical backdrop to allow for products and services to describe themselves as using AI, when in fact they do not. The label is an organising principle in many spheres, public research funding schemes being one of them. However in applied real-world contexts the term AI is less common. For example, Near Future Laboratory's clients **"don't use the terminology [...] it's so vague" (Nova, 2020).**

Since its inception the AI field has undergone periods of excitement which have temporarily attracted huge amounts of hype and research funding. Historically, however, such peaks of interest have been unable to deliver on their grand promises. This resulted in each period of excitement being followed with disillusionment and associated slumps in funding, these have become known as the *AI Winters*. We are currently in a period of excitement, but it is important to note that is not being driven by any major advances in the theory and science behind AI approaches: **"I'm now seeing quite a lot of what was being discussed then [the 1990s] actually materialising now" (Light, 2020)**. Rather, the current boom is being driven by the increased availability of large data sets (often generated through our online interactions) and the abundance of cheap computing power. Compute power and data are the resources necessary to operationalise and exploit *machine learning (ML)* and *deep learning (DL)* techniques, both of which employ so-called *neural networks*.

".. by the 80s there was this programme to develop neural networks. But of course everything was so primitive, there was no processing power, there was no data to train it on, so it was all hypothetical, and again we went into that AI winter. Now here we are 30 years later, we've got the compute power and we've got the data, and the

[4] It is worth making a distinction between the Sci-Fi visions of killer robots and the understandable opposition to the creation of autonomous weapon systems highlighted by The Campaign to Stop Killer Robots https://www.stopkillerrobots.org.

researchers have kept on going developing the neural networks, and it's all come together to where we are today." (Hall, 2020)

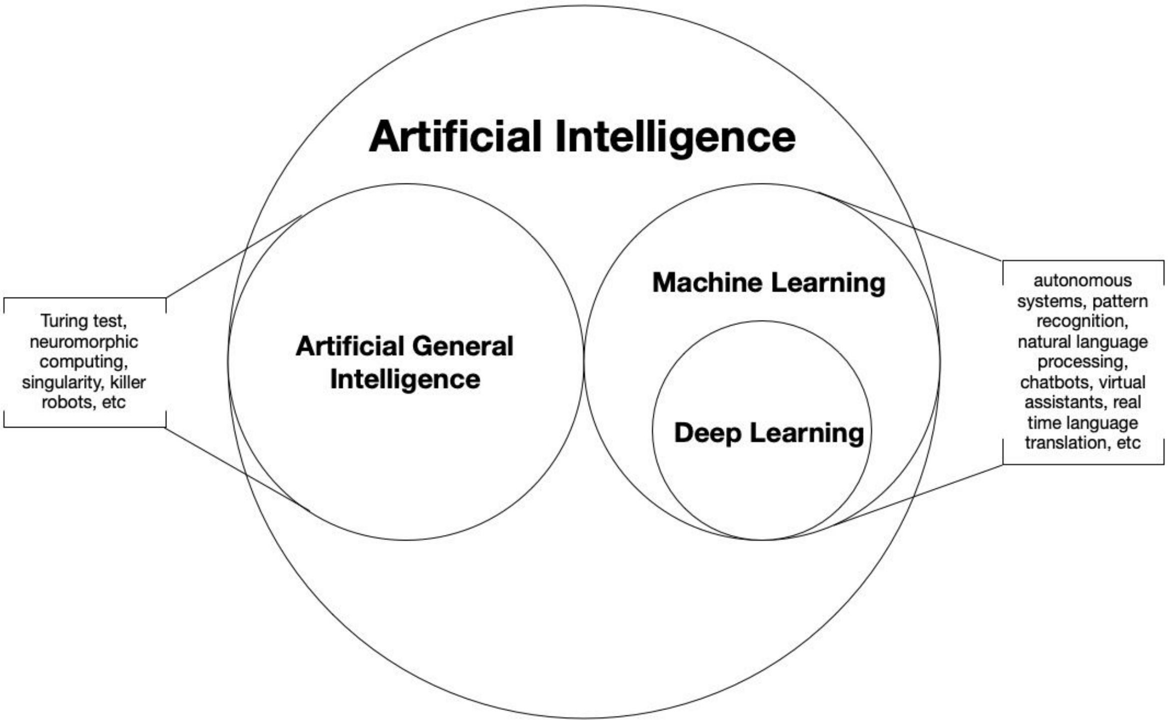


Figure 1. The 'Definitional Dualism' of Artificial Intelligence.

Although the terms AI and ML are often used interchangeably, ML is a subset of AI, and the potential applications of ML represent much of the promise currently attributed to AI. ML works by creating data to train models. These models may be utilised to make predictions (e.g. guessing what word will be typed next when a keyboard is in use) or to generate new data (e.g. creating a life-like but artificial photograph of a human).

ML usually relies on labelled training data. For example we may take a collection of nature photographs. The data is structured so that images which contain Aardvarks are labelled as such. Then, using a classifying neural network, the structured data (combination of images and labels) is processed and the result is a usable model. Such models - assuming the training data was appropriate, the labelling was accurate, the neural network was configured correctly - accurately determine whether new images (i.e. those it has never seen before) contain an Aardvarks or not. The same process can be applied to many different tasks because it can draw upon the vast array of datasets in the world today, this is how ML can be so powerful.

While ML is a data-driven subset of AI, DL, in turn, is a subset of ML. The key difference between ML and DL is that rather than relying on labelled data sets to provide the structure of the data, multiple layers of neural networks manage to extract features automatically and thus creating a nested hierarchy of concepts or abstractions of the source data. While an ML system relies on humans to extract the features (or rules) of classification, in DL the system creates its own rules and tests them internally (see Figure 2). The distinction between ML and DL systems is sometimes referred to as ‘supervised’ (ML) and ‘unsupervised’ learning (DL).

Reinforcement learning (RL) is a third distinct type of AI learning which doesn’t rely on data in the same way. RL algorithms have a measure of success, they can receive rewards, and punishments, and they constantly update and try out new things. If an update results in more successful outcomes then the model ‘reinforces’ that approach (and vice versa). RL systems can be combined with ML and DL systems to great effect, famously powering the AlphaGo systems’s historic victory at the game of Go over Grandmaster Lee Sedol in 2016[5].

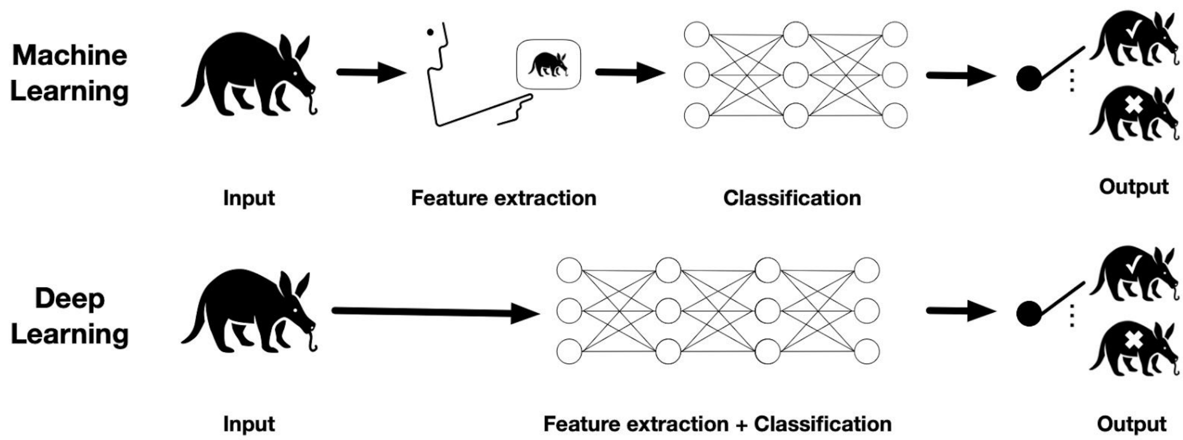


Figure 2. Machine Learning or Deep Learning

All AI systems can suffer from algorithmic bias, a term which describes systematic and repeatable errors that create unfair outcomes. A common misconception is that DL is somehow fundamentally free of human influence because of the way features are extracted automatically. Figure 3 illustrates how this is not the case. Although humans do not control feature extraction directly as they do in ML they are:

- Responsible for selecting the dataset which is used for training;
- Configuring how features are extracted from that data;
- Assessing whether feature extraction is achieved appropriately;
- Providing oversight of the decisions models make in the real world.

Each of these processes is a point at which bias may enter the system. ML systems have the additional risk of label data being biased by the human labellers. The recursion illustrated in Figure 3 shows how AI systems can act to effectively amplify human and societal biases.

An infamous example of this is the COMPAS algorithm. COMPAS is used in the USA to guide sentencing by predicting the likelihood of a criminal reoffending. According to analysis by ProPublica the AI-powered model at the heart of COMPAS predicts that black defendants pose a higher risk of recidivism than they actually do (the inverse is true for white

5 https://www.theguardian.com/technology/2016/mar/15/googles-alphago-seals-4-1-victory-over-grandmaster-lee-sedol

defendants). The company which created the algorithm challenges these results, but given the algorithm is proprietary (and therefore not open to an open forensic analysis) it is hard to discern the truth. It is completely plausible, however, that as per the processes depicted in Figure 2 and Figure 3, human influence and societal biases are reflected in the algorithm.

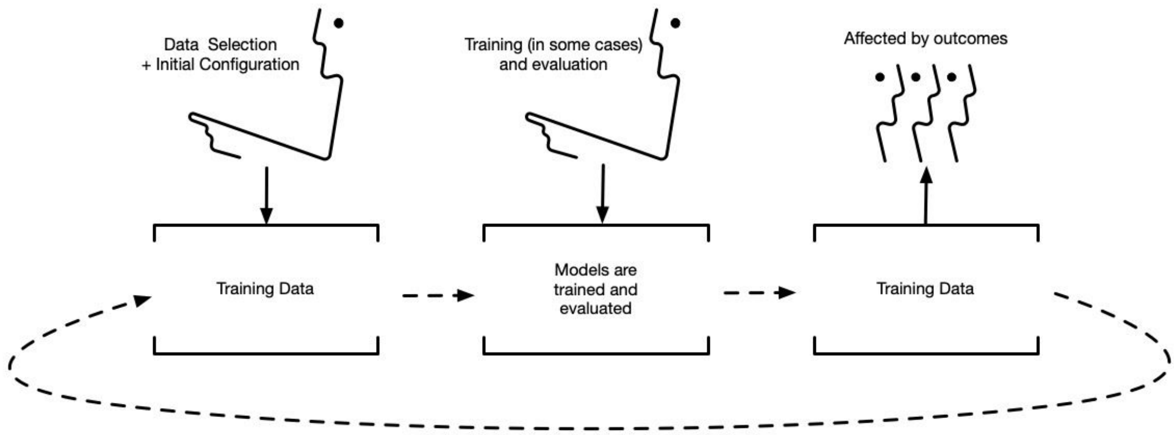


Figure 3 Human-AI Relationships

This example highlights how the underlying structure of AI systems' architecture make unbiased deployments of AI systems a multi-layered and often intractable problem. Transparency is often cited as a way to design AI systems which are ethically sound, however meaningful transparency, or legibility, is extremely hard to operationalise. AI is not only a black box[6] for those affected by their use, in many ways AI is also a black box for their creators. Whether utilising ML, DL or RL training techniques, the resulting AI programs eventually operate in a way that is inaccessible to their human creators. They rely on the interrelation between many thousands of variables which can be computationally tweaked at great speed. The effect of this is akin to multiple layers of AI black boxes nested within one another, hence notions of transparency must be carefully qualified.

Some experts suggest the problem is even worse than nested black boxes: Ali Rahimi (an AI researcher at Amazon and formerly of Google) argues that not only do many creators not understand how their finished AI systems reach decisions (e.g. 'I do not know why the autonomous car decided to drive into the wall') they also don't understand the techniques they used to build those programs in the first place (e.g. 'I cannot explain the algorithm I used to create the AI which decides whether to drive into the wall'). Rahmi describes AI development as being akin to alchemy or using an alien technology.

"There's a place for alchemy. Alchemists invented metallurgy, ways to make medication, dy[e]ing techniques for textiles, and our modern glass-making processes. Then again, alchemists also believed they could transmute base metals into gold and that leeches were a fine way to cure diseases."[7]

[6] In science, computing, and engineering, a black box is a device, system or object which can be viewed in terms of its inputs and outputs without any knowledge of its internal workings.
[7] https://www.livescience.com/62495-rahimi-machine-learning-ai-alchemy.html

While AI has clear potential for societal and economic benefit, it is clear that research is needed to develop more nuanced understandings of how we conceive of AI, how we communicate about AI, and what we should expect from AI.

3.2 AI Guidance Frameworks

The perception of AI as layers of block boxes obscured behind a curtain of alchemy is an obvious challenge for designers of AI systems but also for researchers, theorists, educators, and policy-makers. While the real-world impacts of such AI systems are tangible, imagining what they might achieve before-the-fact, predicting the impact of their results in action, and monitoring how they evolve over time, are conversely intangible. This dichotomy has led to academic researchers,commercial organisations, governments, civil liberty groups, and other interested organisations to promote more considered perspectives for the use of AI[8]. For example Google[9], Microsoft[10], Amazon[11], UK Government[12], UK House of Lords[13], the EU[14], the G20[15], the Organisation for Economic Co-operation and Development (OECD)[16], UNI Global Union[17], Amnesty International (Toronto Declaration)[18], IEEE[19], ACM[20], the Machine Intelligence Garage (Digital Catapult)[21], the Alan Turing Institute[22], and the Ada Lovelace Institute[23] all have their own initiatives for promoting the responsible use of AI.

The proliferation of guidance relating to responsible AI, which are primarily conveyed by the written word, represents a significant comprehension challenge; i.e., discerning what insights are relevant for a given context and how to turn the advice into practice[24]. However, while the spectrum of initiatives is broad, there is much shared ground between them. Recent work by Fjeld et. al. (2020) has distilled a wide range of these documents into general principles and guidelines, the key topics of which are:

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[8] https://inventory.algorithmwatch.org
[9] https://www.blog.google/technology/ai/ai-principles/
[10] https://www.microsoft.com/en-us/ai/responsible-ai
[11] https://www.partnershiponai.org/partners/amazon/
[12] https://www.gov.uk/guidance/understanding-artificial-intelligence-ethics-and-safety
[13] https://publications.parliament.uk/pa/ld201719/ldselect/ldai/100/10014.htm
[14] https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai
[15] https://www.g20-insights.org/wp-content/uploads/2019/07/G20-Japan-AI-Principles.pdf
[16] https://www.oecd.org/going-digital/ai/principles/
[17] http://www.thefutureworldofwork.org/media/35420/uni_ethical_ai.pdf
[18] https://www.amnesty.org/en/documents/pol30/8447/2018/en/
[19] https://standards.ieee.org/content/dam/ieee-standards/standards/web/documents/other/ead1e.pdf?utm_medium=undefined&utm_source=undefined&utm_campaign=undefined&utm_content=undefined&utm_term=undefined
[20] https://www.acm.org/binaries/content/assets/public-policy/2017_usacm_statement_algorithms.pdf
[21] https://www.migarage.ai/ethics-framework/
[22] https://www.turing.ac.uk/sites/default/files/2019-06/understanding_artificial_intelligence_ethics_and_safety.pdf
[23] https://www.adalovelaceinstitute.org/our-work/just-ai/
[24] https://algorithmwatch.org/en/ai-ethics-guidelines-inventory-upgrade-2020/

Privacy - This covers guidance relating to how data is collected, stored, used, managed, and controlled much of which is enshrined in the European Union General Data Protection Regulation (GDPR)[25]. *Privacy by Design* is often cited as a segue from design issues to privacy issues, however when interpreted hubristically as a 'solution', Privacy by Design is a "Heffalump trap" (Lindley et al, 2018).

Accountability - When decisions are no longer being made by humans, who is then accountable for them? This also covers the potential social and environmental impact of the technologies and infrastructures employed by AI systems. Specific topics it would address would include verifiability of decisions, impact assessments, auditability, liability, etc.

Safety and Security - AI systems have the real potential to produce harm, hence ensuring the safety of both the living beings and the environment that such systems operate in, is paramount. A key part of this are the cybersecurity considerations in terms of hardware and software, however given suchs systems are often socio-technological the human factors must be considered as cyber attack vectors too.

Transparency/Legibility/Explainability - Although in some cases these terms are used almost interchangeably they often describe subtly different things. Transparency is concerned with how open the data and algorithms are to outside scrutiny, such that decisions can be verified or challenged (in some cases this openness is suggested to the whole design and development process). Explainability relates how we make AI systems and their decisions understandable, this can apply both in terms of AI designers (so they can make ethical judgements) but more frequently to non-AI experts and users of AI systems. Because of the black box nature of most AI systems, simply making them transparent does not immediately translate to making them explainable, for this reason the use of symbols and signs to make systems to increase the legibility of AI systems is a current area of study (Lindley, et. al., 2020).

Fairness - This primarily relates to AI systems detrimentally affecting or privileging particular populations. This may be due to systems being trained on biased or unrepresentative data. Further problems may arise from assumptions made during the design process in what decisions are directed towards that may produce discriminatory or harmful effects.

Agency - Whilst concerns relating to a reduction of human agency are, arguably, amplified by AI's definitional dualism, many AI guidelines seek to ensure human agency is designed into AI systems. This may be in the form of human review of AI decisions ('human in the loop AI') or the ability to challenge or opt-out of decisions made by the machine.

Human Centeredness - Also described in terms of human values these principles pertain to ensuring that AI systems are designed to work for humanity's best interest and reflect human values in respect to social norms and cultural beliefs and are inclusive[26].

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[25] https://gdpr-info.eu

[26] While the fundamentals of Human-Centred Design are morally clear, recent work relating to 'More-Than-Human Centred Design' is a response to the potential issues which arise when Human-Centred Design techniques result in technology disappearing into the background, which in turn can cause harm for users - this is particularly salient for Internet of Things and AI systems (Coulton & Lindley, 2019).

The potential for Design Research to contribute to the production of guidance documents is clear. Specifically the inherently interdisciplinary character of Design Research catalyses a move away from 'monocultural' perspectives and reflects the seachange necessary to engage with issues relating to AI and Data.

"The companies that are actually making the most progress are actually taking on that experimental task within their organisations and forming multi-specialists, the equivalent in academia of multi-disciplinary teams, that are working together on these hard problems to take what lives at a level of principle like explainability or fairness, and actually operationalise that in the product development process from start to finish." (Vallor, 2020)

Purely technical solutions to socio-technological issues are unattainable, and the arts and humanities have a critical role: **"At the moment I don't see a technical test for bias emerging. It's going to take a whole new group of people. I think the AHRC would be interested in something like that." (Hall, 2020).** A large part of the challenge are issues relating to design; for example how to translate abstract guidance in concrete product choices, balancing technical constraints and against aspirational features, and crucially considering the implications of a given technology's adoption into the future. This role of facilitator is perhaps one of the most crucial challenges that Design Research and Design Researchers can contribute towards.

"If someone's really curated properly the question of who's in the room, then I'd say they're taking it seriously [...] it's often just the scientists that are in the room, and their ability to imagine what the problems could be are very, very limited to a particular context, or a very narrow breadth of possibility based on I guess what they see" (Auger, 2020).

3.3 How are AI systems put to use?

Whilst the specific use cases (i.e. context that they're applied in) of data-driven AI systems are incredibly diverse the way in which the underlying systems operate can be divided into three distinct modes of operation (see figure 4).

Classification - These applications are generally trained to recognise particular patterns in data whether it be from images, audio, text, or indeed any other forms of data. Particular examples include face recognition (e.g. suggested tags on Facebook, or automatic passport gates), voice recognition (e.g. powering voice assistants like Siri or Google Home), customer service chatbots, email spam filters, and - famously - cats on Youtube (using Youtube videos as the training data a deep learning systems spontaneously learned to recognise felines due to the proliferation of cat videos on the platform).

Prediction - These applications identify patterns in current data based on previous data and attempt to predict potential future behaviour or outcomes. Particular examples would include: fraud detection, dynamic routing on turn-by-turn navigation (e.g. Google Maps and Waze), dynamic pricing (e.g. Uber), sales (e.g. predicting will increase closed sales and 'you might like' style product suggestions), media viewing suggestions, and automatic search query completion.

Generation - Based on patterns extracted from training data these systems are used to suggest new possible configurations. Examples include: image (e.g. Google Dream[27], DeepArt[28], GoArt[29]), drawing (e.g. Cartoonify[30]), 3D design (e.g. Adobe Dimensions, Autodesk), synthesised media (e.g. Deep Fakes), Music/Sound(e.g. NSynth[31]), data visualisation (e.g. Activation Atlas[32]), fonts (e.g. FontJoy[33]).

Figure 4. Three modes of AI operation.

Figure 5: Source Image (left), Google Dream (center), GoArt (right)

Considering these modes of AI operation help to bring into focus how the various relationships between emerging AI, Design, and Research are in themselves multifaceted. The emerging social and ethical challenges of AI systems which can predict and classify[34] are good candidates for Design Research which is concerned with interactions, experiences, and services. In this sense, 'Design Research' means 'Design' is the method to explore some other domain. Meanwhile, generative AIs raise issues of direct relevance to professional Art and Design practice, for example graphic design, product design,fashion

[27] https://deepdreamgenerator.com
[28] https://deepart.io
[29] http://goart.fotor.com
[30] https://experiments.withgoogle.com/cartoonify
[31] https://experiments.withgoogle.com/sound-maker
[32] https://distill.pub/2019/activation-atlas/
[33] https://fontjoy.com
[34] It is worth noting that prediction and classification are often the basis of the new generation of AI infused tools being proposed for the digital humanities.

design[35] and architectural design - AI and Data in these domains require research (which may also be termed 'Design Research') because they will undoubtedly alter and change the work and practice of what it is to design. In this sense, 'Design Research' means 'Research' into the practice of design[36].

Whilst digital tools have undoubtedly changed the way graphic designers, product designers, fashion designers, and architects create their designs, because AI is facilitating a step-change where, for some classes of design, millions of variants can be created very quickly. When adopted, this change results in the designers role shifting from *directly* designing to focusing instead on data selection, algorithm configuration, output evaluation and selection (see Figure 3).

Examples of this include Nutella's Unica campaign which generated 7 million unique Nutella [37] labels for jars that were subsequently sold; the complex curves of Zaha Hadid Architects' Heydar Aliyev Center[38] were designed using script-driven geometry engines and AI-powered cranes which were algorithmically managed to optimise the construction of complex building designs.

This shift in role for designers does not mean that human creativity is removed from the process. Figure 3 highlights the human element of AI-supported design processes is crucial: selecting the appropriate starting conditions and making judgments about which of the generated designs most fulfills the brief. This is evident in current creative projects using AI which largely adopt the alchemist approach in that they focus on whether the outcome fulfils their requirements rather than how it produced such an outcome. However, the use of AI in such situations produces considerable challenges for copyright (Dennis 2019) and patent law (Gervais 2020) as the notion of authorship fundamentally disrupted[39][40].

The scope for AI as a generative tool is vast. AI streamlines and enhances animation pipelines, and can even entirely replace deceased actors in live-action films (e.g. Peter Cushing's appearance in the 2016 film *Rogue One*). Elsewhere AI has been proposed as the basis to dynamically create content using object-based media whereby customised versions of broadcast television can be created dynamically in real-time using individuals' personal data (Coulton et al 2019). Generative AI has widespread nefarious applications too. Infamously, so-called 'deepfakes' have been used to make lifelike depictions of celebrities in pornographic films, politicians apparently promoting their opponents, and to make American

[35] https://www.vice.com/en_us/article/vb9pgm/this-clothing-line-was-designed-by-ai
[36] This distinction was famously captured by Sir Christopher Frayling (1993) by using the nomenclature Research through Design (practice-based research), Research into Design (research about design practice), and research for Design (background research that any design process may draw upon such as requirements gathering).
[37] https://www.youtube.com/watch?time_continue=5&v=sHYakhyvJps&feature=emb_logo
[38] https://www.zaha-hadid.com/architecture/heydar-aliyev-centre/
[39] https://www.ipwatchdog.com/2020/05/04/uspto-shoots-dabus-bid-inventorship/id=121284/
[40] https://www.ipwatchdog.com/2020/01/07/epo-ukipo-refuse-ai-invented-patent-applications/id=117648/

actor Bill Hader apparently morph into another actor (Tom Cruise) mid-interview[41]. When applied to text rather than photography, generative AI is also the basis for producing huge volumes of plausible, yet false, fabricated news stories[42].

Classification and prediction are two closely related, but somewhat distinct concepts. They tend to utilise the same algorithms and approaches to AI. The key difference is that a classifier makes a prediction and then based on that makes a decision, while for a predictive AI the prediction itself is the end point. The ways in which AI is put to use for classification and prediction are hugely diverse. Applications which seem relatively mundane such as electronic-passport gates, soft keyboards on smartphones, decisions on whether customers get loans, and email spam filters - all of these often utilise AI-powered classification. Similar processes lie behind dynamic pricing for ride-sharing apps and flight comparison services, route optimisation for turn-by-turn navigation and even lie detectors. In all of these applications, historic data is utilised in order to train the algorithms such that they can make a prediction about the highest price a customer will pay, whether a person is who they claim to be, or whether taking an alternative route will mean reaching the destination more quickly.

The data used to train an AI system, and how accurate decisions based on it are, are intrinsically linked. Properly determining accuracy is rarely discussed and understood outside those specialised knowledge into the workings of AI despite the fact it can have a significant impact on the users affected by its outputs. Discussions of AI accuracy often start with the accuracy of input data, i.e. personal data of a specific individual the AI system then uses to make decisions or predictions about that individual. However, accuracy also applies to AI outputs, in terms of accuracy of decisions or predictions (a more nuanced discussion of accuracy is discussed in appendix 3). Of the three modes of AI previously inaccurate classifiers cause the most significant societal problems, for example wrongly predicting a criminal will reoffend, or determining a customer isn’t fit for a loan. Conversely the more accurate generative AIs are, the more their disruptive potential is realised (e.g. deepfakes). AI’s definitional dualism exacerbates poor understandings of accuracy, often leading users of AI systems to hubristically believe they are infallible.

Whilst this overview highlights many contexts which AI can be applied to, the report is scoped specifically around Design Research activity. Based on the experience of the interviewees the report describes what research is currently happening and where there is an opportunity to utilise Design Research to build capacity to strengthen and expand upon the UKs current capabilities in relation to AI and Data.

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41 https://www.theguardian.com/news/shortcuts/2019/aug/13/danger-deepfakes-viral-video-bill-hader-tom-cruise

42 https://www.theverge.com/2019/11/7/20953040/openai-text-generation-ai-gpt-2-full-model-release-1-5b-parameters

4. Design Research and Funding Landscape

Rooted in the Design Science movement of the 1960s, Design Research is still - relative to long-established disciplines like Philosophy or Mathematics - very immature. It evolved quickly and began to proactively address “wicked problems” (Buchanan, 1992), and empowered to respond to “uncertainty, instability, uniqueness, and value conflict” a distinct epistemology and philosophy for Design Research began to emerge (Schön, 1983) which recognised being that “messy and complex” does not have to compromise rigour (Rodgers, 2016). The “designerly” (Cross, 2011) way of knowing “has its own appropriate culture” yet does “not completely disregard other cultures” (Rodgers, 2016). On this foundation Design Research has flourished in the early 21st century, providing the methods and ideology to deliver diverse, interdisciplinary, world-class research (Cooper, Dunn, Coulton, et. al., 2018). The history and structure of the Design Research field has a direct influence on how it is funded, and what it achieves. Inversely the funding of Design Research impacts upon the makeup of the field itself. In this section we discuss this landscape in order to contextualise recommendations for potential Design Research oriented investment opportunities.

4.1 Where is the Design Research?

As active Design Researchers ‘we’ (the authors of the report) are immersed in this burgeoning community through our positions at Lancaster University’s ImaginationLancaster research lab. The lab itself has recently received an investment of £7.6m in order to “explore and demonstrate how cutting-edge design research can create a healthier, more prosperous and sustainable world”[43]. Moreover through a £1m AHRC-funded Design Priority Area Leadership Fellowship[44] and a £1.2m UKRI-funded Future Leaders Fellowship[45], both of which are hosted at ImaginationLancaster, the department is itself a significant centre for Design Research. Notwithstanding our department’s success the focus of this report is the research beyond our own purview, outwith the broader research community. Hence, the report aims to build a complete picture of the Design Research landscape through our interviews. However, to further triangulate the overview data from UKRI’s Gateway to Research portal[46] was also considered.

Gateway to Research is a repository of publicly funded UK research and lists over 32,000 active research projects from a variety of funders (e.g. EPSRC, NERC, MRC) achieved through various delivery mechanisms (e.g. Centres for Doctoral Training, Small Business Research Grants, Fellowships). The data palpably reveals the scale of investment in UK research. For example with over 200 active projects valued in excess of £10m, over 18,000 projects valued up to £100,000 and nearly 11,000 projects valued between £100,000 and

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43 https://www.lancaster.ac.uk/news/new-13-million-project-goes-beyond-imagination-in-tackling-world-issues
44 https://gtr.ukri.org/projects?ref=AH%2FP013619%2F1
45 http://designresearch.works/
46 https://gtr.ukri.org

£1m. While the current portfolio of research is impressive, the aspiration is to increase the share of UK Gross Domestic Product spent on research and development from 1.7% in 2016 to 2.4% by 2027. As that target is pursued AI and Data will become increasingly a cross-cutting area of relevance spanning multiple disciplines and contexts. Moreover, the role of Design Research will become increasingly relevant as the adoption of AI technologies amplifies the need to focus and apprehend technology's broader impacts on society.

The Gateway to Research provides access to data on a huge number of research and development programmes, however, it also highlights some clear pitfalls in the efficacy of using this dataset for reporting on the state of active Design Research relating to AI. For example, querying the 32,000 active projects with the search term 'Design Research' returns only 33 projects. The number of projects returned goes down to 2 if the search is constrained to projects containing both 'Design Research' and 'AI'. While both projects - one a doctoral studentship and one a Centre for Doctoral Training[47] - included in this search do, indeed, incorporate elements of Design Research and AI, the total of two projects is inconceivably low. If the search is relaxed to simply 'Design' and 'AI' then a more plausible 188 projects are returned, of which 21 are funded by the AHRC. This group of 21 projects comprises 1 fellowship, 5 large grants, and 15 studentships. Drawing concrete conclusions from this cursory look at the Gateway to Research would be ill-advised, but what is certain is that only 33 projects include the specific keywords 'Design Research'. If there are, in fact, more than 33 entries in the database which would sensibly be labelled 'Design Research', then a proactive shift in how such projects are labelled and described is necessary. Recent work based on Gateway to Research data by Rogers, Conerney, and Mazzarella (2019) utilised a similar search strategy. Based on our work this is the only practicable way to utilise the data as any further constraint (i.e. searching for 'Design Research' rather than simply 'Design') would result in a restrictively small data sample. The consequence of this search strategy, however, is an increased noise-to-signal ratio, i.e., the data includes examples which mention Design, but which are not necessarily Design *Research*.

Elaborating on the noise-to-signal issue, if we consider the projects which are returned for the search terms as 'Design' and 'AI' (i.e. those which we would expect to be most closely aligned to this report), then *none* explicitly state that they are about or utilise 'Design Research'. For example the fellowship which was included in the search will, coincidentally, utilise an output from a prior Design Research project (*Ethnobot*), but its role in the fellowship is as a tool in service of an unrelated question (which relates to evaluating arts projects)[48]; the *InGame* Hub (part of the Creative Industries Clusters Programme) appears in these search results because of the occurrence of the term 'design' in reference to designing game elements; the *StoryFutures* project appears due to a reference to User Interface Design; and the terms Participatory Design, Co-Design, and Design Innovation are why the various studentships appear in the search results. Curiously, however, whilst none of these entries on the Gateway to Research *explicitly* say that they are using Design Research, the majority *are* using practice-based methods, leveraging material explorations, and building on constructionist epistemologies in order to produce knowledge - all hallmarks of a Design

[47] See https://gtr.ukri.org/projects?ref=studentship-2114888 and https://gtr.ukri.org/projects?ref=EP%2FS022325%2F1 respectively.
[48] See https://gtr.ukri.org/projects?ref=AH%2FT002794%2F1

Research approach. Hence, it is clear that in some (perhaps most) cases the Design Research projects which are documented in the Gateway to Research do not self-describe in a way that makes them discoverable as examples of Design Research[49].

Notwithstanding the difficulty of assessing Design Research based on Gateway to Research data there is an active and vibrant community of Design Research in the UK which aligns to issues arising from AI and Data. Across the UK at centres such as Lancaster University's *Imagination*, the *Mixed Reality Lab* at University of Nottingham, and *Design Informatics* at the University of Edinburgh, Design Researchers lead and participate in a huge array of projects and collaborations. The interviewees we refer to in this report provide an incredibly rich purview of the gamut of Design Research, spanning academic/non-academic work, contrasting approaches within the field, disciplinary backgrounds, differing research contexts (albeit related to the theme of AI and Data), and various funding models (refer to appendix 1 for a brief introduction to some of the projects the interviewees are involved with).

4.2 Where is the Money?

In order to understand the potential for investment in Design Research we asked interviewees to explain their significant sources of income (the related topic of partnerships is discussed in section 7 of the report). The majority of interviewees are currently, or have been, based at UK further education institutions. Of those with a track record of attracting funding in the UK (Shannon Vallor was an exception here, having only recently taken her post) the overwhelming majority reported that the AHRC and EPSRC were their primary sources of public funding, with the ESRC and European funding also supporting a range of Design Research in a handful of cases.

While the majority of interviewees had attracted funding from both AHRC and EPSRC, which council was the most significant for given individuals differed somewhat. Interestingly the two interviewees with the closest historic affiliations with AHRC were, respectively, based in departments of Engineering and Media and Communications. Of the remainder (majorly in Design and Computer Science departments) the primary source of funding historically has been the EPSRC (notwithstanding the recent £5.6m AHRC Creative Informatics grant awarded to Design Informatics at University of Edinburgh). Although all the interviewees deviated from these patterns in some way - most commonly attracting funding for doctoral students from somewhere other than their primary funder - it was clear that among the Design Researchers we interviewed, the EPSRC funded the majority of the work. The propensity of the cohort of interviewees to pursue funding from the EPSRC further qualifies why our search of the Gateway to Research (which was filtered according to AHRC grants) yielded so few results. In a minority of cases significant amounts of direct funding came from the private sector (discussed in section 7 of the report).

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[49] It is possible that the multiple interpretations of 'Design Research' (e.g. both research *into* Design-and-related disciplines, as well as conducting Research *through* Design, into a *non-design* discipline) is related to this challenge, but to address that question is beyond the scope of this particular enquiry.

Design Research applied in AI and Data contexts clearly crosses the imaginary conceptual boundaries between the funding councils; while Design Research's foundation in Art and Design is unavoidable, it is widely applied to understand and contribute to technologically-powered change (which in turn, often draws upon Engineering research). While there is a tendency toward EPSRC funding of AI and Data Design Research, the reasons behind this are not straightforward. At one extreme is the perception that, despite appearing positive, AHRC funding is inaccessible: **"whenever we talk to anyone from AHRC they always sort of speak quite highly of design and how they want to support design, but every time we've put a proposal in we get knocked back [...] EPSRC we find much easier" (Gaver, 2020).** One perception is that the AHRC tends to fund the **"lone scholar"** model, which **"lends itself to do more of the design history kind of humanities focused design research, and less so the more let's build fancy new exploratory technologies" (Kirk, 2020)**. The Digital Economy programme (which is cross council, but majority-funded by EPSRC) in particular was cited as being the source of **"the actual big ticket funding for more design engaged research" (Kirk, 2020).** A number of interviewees raised questions about the efficacy of the AHRC peer-review process. This covered a lack of confidence about finding qualified reviewers in the peer-review college. The prevalence of reviewers whose disciplinary prejudice is toward art history and non-technical subjects was raised as a point of possible concern. Conversely, however,, for some participants the AHRC was their primary source of funding and the AHRC's disciplinary alignment was, sometimes, seen as advantageous:

"I would apply to the AHRC if I had the time to write something, I'd probably be looking at them first, rather than trying to make something look engineering-ly enough to go into the EPSRC" (Kirman, 2020);

It should be noted the perspectives represented in the report mainly reflect the participants own large multi-investigator research grants. Hence, a limitation of the report is a lack of representation from AHRC-funded doctoral research in the AI, Data and Design domain - which in numerical terms (as opposed to volume of funding) likely represent the largest quantity of AHRC-funded Design Research projects. In order to understand that particular landscape a specific review of doctoral research would be necessary.

5. Skills

The report addresses skills and training in a number of different ways: reflecting on the disciplinary background of the interviewees to explore what Design Research is and what skills are necessary to do it; an exploration of the specific skill set necessary for AI and Data centric Design Research; reflection on University-based training pipelines to support the next generation of Design Researchers.

5.1 What is a Design Researcher?

Among the interviewees, despite acknowledging they contribute to the milieu of Design Research, a number of interviewees were reticent to self-identify as a Designer or Design Researcher. In some cases this was because interviewees considered that they researched the topic of Design or researched the topic of Design Research as a subject, but, that this did not make them a Design *Researcher* per se: **“I engage in some design research but normally through other people [...] I wouldn’t count myself as a designer in any normal sense” (Reeves, 2020).** Ewa Luger said **“I'm not a designer”** but went on to say **“I work with designers and I apply design methods, and have been doing for maybe like four years or so I guess, slightly longer” (Luger, 2020)**. The inference of this statement seems to be that one can *utilise* the methods of Design or Design Research, whilst not ‘being’ a Designer. Notwithstanding the clear contributions that interviewees are making to the Design Research field, a tentativeness about identifying as Designers was repeated: **“I never would have considered myself a designer” (Kirman, 2020); “I'm not a trained designer” (Light, 2020); “I don't work in an academic design field [...] I think of that as practice based research, because I don't make stuff, I make experiences” (Powell, 2020).**

A wide range of disciplinary backgrounds were represented including Industrial Design, Design Interactions, Fine Art, Human-Computer Interaction, Games Design, Artificial Intelligence, Filmmaking, Philosophy, Industrial Design, Policy, Media Theory, Psychology, and Ethnography. Unsurprisingly, this diversity is echoed in the departments, organisations, and institutions where individual participants are based. While 6 of our interviewees are attached to organisation units which are explicitly related to Design, the remainder are hosted departments such as Engineering, Theatre, Film and Television, Computer Science, Philosophy, and Media Communications. It should be noted that while diversity exists in perspectives on design these are all still predominantly white western perspectives. Design Research, as with much of University-based research in the UK, is not ethnically diverse, for example fewer than 1% of University Professors in the UK are black[50]. Given AI systems’ propensity to amplify bias, this inequality is particularly vivid. Funders are part of the structural disadvantages that maintain marginalisation, and should pay attention to sustainable means to strive for increased equity.

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50 https://www.theguardian.com/education/2020/feb/27/fewer-than-1-of-uk-university-professors-are-black-figures-show

The diversity (of perspectives on Design) and lack of homogeneity initially makes it difficult to infer generalisations about the skills and training necessary to be a Design Researcher. However two additional framings shed some further light on the matter. First, it is important to consider the ambiguity imported into the conversation by the conflation of research that is *about* Design, and Research which is conducted *using* Design or Design-inspired methods. Second, all of our interviewees had mutli-disciplinary attributes, which may, or may not, include training in Design. In this sense the unifying kernel of Design Research does not relate to specific practices, but to a flexible and dynamic epistemological sensitivity that draws upon multiple perspectives:

“..basically there's a whole lot of things that come together when you put the arts and humanities together”. These factors act to “‘**surround’ design, rather than necessarily being core to it.” (Light, 2020).**

The panoply of perspectives which Design Researchers may incorporate into a project draws upon an equally open-ended range of potential skill sets. Despite this heterogeneity, it does pivot on a shared appreciation:

“We've got people who are really great product designers but who can't do electronics that well [...] we've got creative technologists who are amazing with the technologies, but they're not graphic designers. So everybody kind of has their own mix of skills [...] you can't just find anybody, you have to have somebody with the right flexibility to work with designers” (Gaver, 2020).

The connectivity between creative design processes and the exploratory research processes, sometimes couched in multidisciplinary perspectives, was a recurring theme:

“I don't know where research ends and design starts” (Jain, 2020).

In some cases interviewees cited their *non* Design training as key factor in their research practice:

“What I find interesting in framing the Near Future Laboratory work here as design research, is that it's partly things that matured over time in our practice. It's also a thing that evolved through inspiration [...] by the way we've been trained in engineering and social sciences.” (Bleecker, 2020).

One prevalent perspective on Design Research casts design *practice* as a hugely important aspect, even if the desired outcome is research insight (as opposed to a usable or saleable product):

“For me design is about the practice, how do we maintain that aspect? [...] design is starting to be used to ask questions and participate in philosophical investigations about technology, it's a step into a slightly new terrain.” (Auger, 2020).

“... we are heavily practice based. Everything that we do in our studio is legered as a traditional design practice. Most of the people that work in our studio for instance,

they're not traditional academics, they're all design practitioners [...] it's about how you then begin to articulate that as research I guess" (Boucher, 2020).

"... the process itself I think works best when it's basically just a design process [...] you go through a process of trying to understand the situation or context, come up with ideas for how you might make something that speaks to that situation [... and] actually resolve it in design terms." (Gaver, 2020).

The work resulting from **"the traditions of crafting, of making, of working in workshops, of doing sketches"** can clearly **"in the right context be articulated as research" (Vines, 2020)**. Meanwhile, some practitioners are moving beyond the (physical) artefact and to work around 'soft' design practice such as service or policy design:

"**The challenge I've had with design is it has assumed that artefacts might be part of design research [...] there's a nice opportunity now perhaps to think about what service design for the digital economy, or service design for data driven innovation looks like" (Speed, 2020).**

Whether the practice element centres on physical artefacts or soft designs, the research element of Design Research practice emphasises the need to **"articulate how this is located into a constellation of other things out in the world" (Vines, 2020).**

5.2 Technology-Focused Design Research

When considering the finer-grained question of skills for Design Researchers specifically working around AI and data it is clear that having a 'material' understanding of the nature of AI and data is important: **"Any sort of expert design practitioner would articulate in very intimate terms the nature of the material that they're engaging with [...] I think the same would be in the case of AI or using data" (Vines, 2020).** The need to understand the qualities and attributes of a material, without necessarily needing to have the skill to work directly with the material, is not a new mechanic for designers:

"I don't see that the approach would need to change much from the way a designer was operating in the 1930s. If you want to get a part injection moulded, you don't need to understand how an injection moulding system works, you need to know what objects can be injection moulded, what's plausible, and then you would work with an engineer who'd go and do the engineering side to realise that. I think with AI it's a similar kind of problem, you don't need to be able to write complex algorithms as a designer, but you need to be aware of what an algorithm is capable of." (Auger, 2020)

Whilst the technical skills to work directly with AI isn't *necessary*, depending on whether a Design Research is speculative, or striving for 'in the wild' research, technical input can be highly desirable: **"it would be great, on our kind of lengthy to-do list I think is we'd be really happy to find somebody who simultaneously was good at stuff like data and machine learning" (Gaver 2020).** While the value of technical AI and Data skills to a Design Research project should not be underestimated, a sensibility as a Design Researcher an equally important aspect, **"If you had someone that was an AI expert,**

they'd also need to be multi-disciplined in some way themselves [...] if they work with us they wouldn't be doing AI all time" (Boucher, 2020).

By bringing the ability to conceive of AI and Data in terms of a malleable material which can be designed 'with', Design Research practitioners **"create a design space which you populate with alternatives [...] a play of possibilities [...] that's something that in computing and engineering I think they do a lot less of" (Kirk, 2020)**. Hence the value that Design Researchers in interdisciplinary projects transcends the technical and moves into a **"really useful role in synthesising understanding"**, it **"materialises the research problems"** and **"acts as a fulcrum in really useful ways" (Kirk, 2020).** This synthetic ability of Design Research was highlighted multiple times as a key strength, particularly with respect to AI, Data and technology in general: **"how a [computer science] researcher understands AI and data, and how a human understands AI and data, is very, very different. That's what design research is really good at" (Kirman, 2020).** Even when working in very technology-centric contexts, the core skills of Design Researchers relate to synthesising perspectives in order to ask salient questions at the intersections of multiple disciplinary boundaries: **"So for me the ideal project is if I get to sit next to the AI researcher who's writing the code [...] I want to be sitting there and understand why they want to make this work? What are the implications? What are they thinking about? Why does it matter?" (Jain, 2020).**

5.3 Creative Industries and Education

An aim of the report was to explore the impact of AI on the landscape of the creative industries, we examined this issue through the lens of the implications of AI and Data on further education in Design-related subjects.

Design's strength at cohering multiple perspectives and sense-making around issues which are part social and part technical was reflected in discussion about education, as well as research: **"I have kind of found a real advantage of bringing the humanities into design education" (Jain, 2020)**. However, it was also reported that this space may need further attention; **"there's effort that could be made into improving design education so that designers coming through are more sensitive to what the implications of AI might be"** and that courses are already adapting to AI being more prevalent "**We've specifically put a module into that programme [...] so that they have some awareness and some sensitivity to what it is that they might be designing with and for**" **(Kirk, 2020)**. Many of the challenges arise from deficient data literacy **"they're designing a system, but they still don't really necessarily understand what you can do with data [...] it remains ethereal; it has that invisible quality, even for designers" (Light, 2020).**

In Design Schools, a wide range of taught programmes at undergraduate and Masters level are adapting. However, arguably there is currently a **"blind spot"** which to be addressed requires that **"[AI] needs to be woven in at some point [...] not the core training because it won't be for everyone, but certainly I think it has to be a specialism" (Vines, 2020).** Part of the process of filling in this blind spot may involve clarification around AI's definitional dualism:

“..one of the things that I think is particularly important, especially with AI, is trying to avoid a tendency towards [...] the kind of like killer computer kind of idea. I think a lot of discourse around AI immediately goes to the ethics of it, which is very sensible, but it's often framed around these potentially catastrophic consequences of Terminator-like technologies” (Kirk, 2020).

It was also acknowledged that AI will potentially have an affect on various design disciplines through its incorporation into the tools of the trade. Whilst its likely that the alchemic approach to understanding AI-infused tools may be prevalent, to exercise greater control some literacy in the operation of AI systems would be highly beneficial in their education:

“There's a critical discourse that has to be had with students around that in terms of them just understanding what is that doing to their practice and where that practice was traditionally [...] the power of AI enriched or enabled tools as part of the design process as well at the fundamental level of [for example] Photoshop doing some things on your behalf now” (Vines, 2020).

Across the spectrum of Design Research the sentiment **“you have to know a little bit about everything” (Light, 2020)** and **“I think it's like anything, the designer doesn't necessarily need to have all of the skills, but they need to have a knowledge of what the subjects are” (Auger, 2020)** is pervasive. The flexible ontological foundation of Design explains how Designers make meaningful contributions to AI and Data research without requiring a *working* knowledge of AI systems or the data structures which enable them. It also underpins the shift in the broader role for Design: **“up until this moment in history really been about creating demand, and about creating the conditions for continued productivity and ever increasing productivity”** however, we are currently in a **“moment of instability [...] and designers are trying to work out how to balance what they think is the right thing to do with the demands of the larger political economy” (Powell, 2020).** To understand the full extent of this shift’s impact on AI, Data, Design, education and the Creative Industries requires a proportional and targeted research-based exploration beyond the scope of this report.

6. Research

In this section the focus of contemporary research questions is discussed in order to identify the nature of salient gaps in AI and Data knowledge that Design Research is contributing towards. As this report has already highlighted there are a plethora of guidelines and principles essentially to help frame values which should be foregrounded during the design, testing,evaluation, and deployment of AI systems (Fjeld et. al., 2020). The multitude of projects that the interviewees are engaged with - not to mention the wider field, including doctoral research - contribute towards these efforts in a wide variety of ways. A currently *unmet* need, however, is the need to bridge the gap between theory and practice (see recent Digital Catapult report, *Lessons in Practical AI Ethics*[51]). By delivering practical examples, and leveraging a *material* engagement with AI and Data, Design Research has a significant opportunity to help bridge that gap: **“It's going to take a whole new group of people. I think the AHRC should be interested in something like that. What does that mean? What are the frameworks we're going to develop? How do you test the bias?” (Hall, 2020)**. The unique quality of Design Research as a **“practice at which the formation of this techno-systemic frame is a really important moment” (Powel, 2020)** is what makes it especially well suited to specifically the kinds of challenges AI poses: **“working with other people who can help us examine that notion of purpose, whether that's the anthropologists or psychologists, whoever it might be. Design for me is perfectly placed to straddle those worlds. But we have to get better at making that case” (Auger, 2020).**

Among the interviewees projects, research questions are usually derived through some kind of collaboration with an external partner. In the case of research council funded work these collaborations often take the form of project partnerships (which are discussed in more detail in section 7), while for work conducted by our non-academic interviewees by organisations such as Superflux and the Near Future Laboratory, the collaborations tend to be negotiated around a more traditional client/design brief model. The scale of these collaborations varies dramatically, for example from Design Informatics’ partnerships with Legal and General, RBS and Tesco Bank through to University of York’s collaboration with community theatre groups. In addition to the diversity of scale we note that, reflecting the multitude of meanings and practices which make up Design Research, there is a similarly diverse network of research priorities and agendas. For example, these encompass both societal and economic issues (which are being explored *with* Design research) and challenges relating to design practice (which impact directly on Design Research itself as well as non-research Design practice). Hence, within the gamut of related work there are many attributes which have a tangible impact on the quality and motivation of different research agendas.

While the detail in the minutiae is significant, the overarching research questions are relatively straightforward to codify. AI is facilitating and catalysing rapid shifts in the world we live in. This extends and accelerates the related, but distinct, societal shifts associated with the adoption of the Internet, the world wide web, and the Internet of Things. Attempting to understand how to optimise the societal shifts resulting from the adoption of AI (where the

[51] https://www.digicatapult.org.uk/news-and-insights/publication/lesson-in-practical-ai-ethics

term ‘optimise’ is deliberately subjective and context dependent) is the unifying research space. Within that broad church large organisations - for example, financial institutions, technology multinationals, local governments - seek help from Design Researchers. In the case of Tesco Bank they are **“just trying to hold up a bank with various apps to allow people to move money into different places to keep their lives together”**, issues which they are **“locked in”** to, however through collaboration with Design Researchers they are empowered to **“re-question what and how they are designing. [by asking] What's the imperators to which they're designing those things?” (Speed, 2020).** The theme across our University-based interviewees was that the kind of contribution University’s offer through collaborations is research with a more exploratory character, providing **“.. alternative ways to think about things” (Gaver, 2020)**:

“I've had these discussions with companies I suppose in the not too distant past where if they're going down the product route then yeah we can help. But actually not being a commercial partner, we're a university, we're something different [...] We are very good at providing a large-scale future focused research space where people can come and in a low risk way try out problems. They can explore problem spaces and they can try new technologies” (Kirk, 2020).

This kind of open-ended creative exploration at the intersection of society and technology is something that previously was well funded by the tech sector, however in recent years such centres have refocused on product-oriented investment. **“The classic and most well-known example is Xerox PARC [...] they've all shut down over time, or in the case of PARC it's been turned into a separate company and basically mostly does consulting now and doesn't do basic research at all, as far as I know” (Reeves, 2020)**. While these ‘freewheeling’ corporately-funded centres are primarily a thing of the past, in its place the tech sector tends to invest in, or buy out, start-up companies. By purchasing embryonic apps, services and techniques, they use start-up culture as a way of externalising research risk. However, this approach means limits their investments’ ability to address larger systemic and macro research questions:

“.. start-up culture can solve certain kinds of problems [...] you cannot start-up your way out of a digital infrastructure problem [...] Start-ups are very good at making apps or whatever, other stuff like that, small things, but for really wicked tricky problems they are not” (Reeves, 2020).

On another part of the spectrum of collaborative publicly-funded Design Research a range of more cultural and community oriented work exists. For example, as part of a European Cultural Fund project the University of York work on a **“no staff cost”** basis in order to use their Design Research practice for direct impact, for example **“the theatre company or whoever, to work and figure out if something's going to work for them, or if they can figure out a way to use it effectively. They take it on and then they make it into a production if they're happy with it” (Kirman, 2020)**. In this community domain the research still gravitates towards **“trying to help people understand technologies before they actually have the implications that are projected for them”**, which is crucial because **“technology is now shaping society quite as much as any political party**

might be", and reflective of **"delight and fascination at what's possible"** but also **"a new digital divide or social divide" (Light, 2020).**

The vast range of Design Research draws upon a rich toolkit of methods and approaches including service design, experience design, speculative design, co-design, interaction design and human-centred design. These are applied in a broad selection of contexts to equally broad questions including, **"Who's accessing that data? Where's it being held? Who else can view it? Actually do I have any sort of say on that at all? [...] What is that training data, and how has it been trained, and where has it been collected from? What is it at that intimate level of what the fundamental data points are?" (Vines, 2020)**, collectively these contribute to the grand challenges around algorithmic bias, fairness, agency, and what the implications for transparency, legibility, and explainability are. It is clear given both the background discussion in the report, the wide array of existing work, and the huge spectrum of active Design Research in this space there are opportunities in a plethora of application areas or contexts for Design Research to make meaningful contributions.

Unifying this work, and bringing particular relevance to contemporary issues around AI and Data is Design Research's aptitude to materialise and make tangible otherwise intangible and diffuse problems. Whether observed from the perspective of a large multi-national or a smaller local community, the gaps in knowledge around AI and Data which Design Research speaks to best, relate to bridging the gap between theory and practice.

This discussion of the research landscape has focused on the higher-level purview of the AI and Data space. Another active area of research, which is related, explores the impact of AI and Data on Design itself. As discussed *a priori* (see section 5) there is an intrinsic interplay between the creative process of 'doing design' and the exploratory practice of 'doing research'. In Design Research the two intersect in a multitude of ways. **"The power of AI enriched or enabled tools as part of the design process" (Vines, 2020)** clearly has an impact on what it means to be creative. Moreover being able to meaningfully conceive of data, from a design perspective, is an idea being grappled with across the board: **"I think within design training there's perhaps less sensitisation towards working with data" (Kirk, 2020)** with the concept of **"data as a material" (Gaver, 2020)** being a recurrent theme. To fully map or assert conclusions about the coordinates of these questions of research *into* design is beyond the scope of this report, however it is most certainly a key area for further clarification.

7. Infrastructure and Partnerships

Identifying research centres of excellence in this domain is not straightforward as world-class work is often associated with individuals (who may move) and/or projects (which may cross institutions). Such projects often rely on interdisciplinary relationships to get the most out of the Design Research elements. Hence to specify single centres often doesn't make sense. Additionally, the perspectives of the interviewees on what constitutes their Design Research is varied, so codifying that first is - arguably - a necessary preliminary step when trying to identify centres of excellence. Those who principally saw their engagement with design as the adoption of creative methods to address challenges in novel ways to provide alternative perspectives, are in a very different category to those who considered themselves as designers and engaged with particular topics through reflection upon their practice. Whilst there is often overlap of methods between these perspectives, particularly in participation and co-creation, they predominantly differ in the value and epistemological relevance of their contributions.

The centres that our interviewees are affiliated with are certainly among the centres of excellence in their respective fields, however the full extent of picture is more nuanced. To elaborate: Superflux and the Near Future Laboratory are both respected studios outside of the academic sphere, with others including Changeist, Design Friction, Situation Lab, to name a few. The Interaction Research Studio is one of the most revered practice-led Design Research centres, but both Northumbria University and University of Edinburgh - among others - are also centres of excellence in that space. However, both Northumbria and Edinburgh Universities are also leaders in other, less practice-based, Design Research (e.g. exploring innovation, service design, and social issues using Design-led techniques). Specific projects, for example Paul Rodgers' Design Priority Area Leadership Fellowship or Design Informatics' Creative Informatics work, are exceptional projects in their specific niches. Just as projects are sometimes the focus of excellence, individuals often embody leadership and excellence, for example Ben Kirman's unique position at the intersection of Game Design, Design Research and Human-Computer Interaction. As noted previously, yet not detailed in this report, there are also a significant number of Design Research projects funded by the AHRC are in the form of doctoral research and are distributed widely.

In sum there is an extensive community of Design Researchers and excellence can be attributed to individuals, projects, and approaches. To properly articulate this additional in-depth research to fully map and explore this landscape is necessary and would provide a framework and vocabulary to more specifically articulate the nature of the UK's centres of excellence.

A variety of perspectives reflect the expertise, knowledge, and practicalities of the interviewees, their work, and what those factors tell us about potential investment opportunities. First it is clear that collaboration with non-academic institutions, as part of publicly funded research, is the bread-and-butter of Design Research. Design Research thrives on such collaborations and they are central to what Design Research achieves. Such collaborations provide the contexts to which Design Research's exploratory and divinatory prowess is applied. Depending on the specific configuration of stakeholders (e.g. research institutions and partners) value is added through a number of different mechanisms. In the case of the non-academic interviewees, their relationships are akin to a client/agency/brief model where Design Research, which has an obvious value to the client (e.g. for planning, exhibition, product development, strategy development), is commissioned and paid for. In the case of the academic interviewees the relationships are a little more complex. For example, research around a particular issue will ordinarily result in impact on the domain of study (e.g. autonomous vehicles) but *also* have academic impact (e.g. journal articles about autonomous vehicle theory). In some circumstances impact case studies are the only outcome of interest to the academic institutions, hence the University institution gives an 'in-kind' or nominal-cost contribution to a collaborating organisation in order for a project to be delivered. Interviewees were mindful that, depending on the nature of collaboration there maybe an onus to ensure the partnerships are reasonably equitable:

"I've worked with lots of different kinds of organisations, small independent folks and barely-existing civil society organisations, I always to try to make sure that the powerful partners, which are usually the Universities, are able to properly support the less powerful partners" (Powell, 2020).

Nonetheless, in-kind contributions typically work the other way around as well, with non-academic partners offering staff time or access to resources to academic Design Researchers. In these circumstances, most frequently the benefit to the academic institution is the invaluable access, **"providing you with data, providing you with expertise, providing you with a use case" (Hall, 2020),** which is absolutely necessary to conduct certain types of world-class research. Such in-kind contributions through project partners are generally seen as significant and productive:

"[We] leverage pretty extraordinary amounts of resources [from] project partners on Research Council bids [...] they provide a lot of service in kind as it were. That's been extremely helpful." (Gaver, 2020).

The non-academic partners may be motivated to make such in-kind investments for a variety of reasons: for example, as a low-risk opportunity to take a more exploratory (less product-driven) perspective on their business; to maintain established collaboration relationships (including through industry placements for students); to facilitate research and development which wouldn't otherwise happen; to benefit public relations by being associated with notable public research programmes. In-kind investment are the prevailing type of private investment:

"Most of the time it's the usual stuff, costs in kind, those sorts of things, access. That's normally what happens. I wouldn't say we get majorly funded by anyone else, not in a big way, apart from research councils." (Reeves, 2020).

In contrast to in-kind contributions - which are common, and arguably *necessary* elements of significant research council grants - direct funding or cash contributions are much rarer and are sometimes perceived as difficult, e.g., **"after lots and lots of work and with a lot of uncertainty, you can get a small amount of money" (Gaver, 2020)**. The interviewees had various reflections on this issue which are relevant to the question of where there are private investment opportunities into Design Research. As discussed in section 6, the rise of ‘start-up culture’ appears to be linked to a marked reduction in corporate investment in fundamental research. Hence, opportunities are scarcer than they were. Some interviewees raised issues relating to the contrast in academic and corporate cultures, noting that **“often when a company funds you directly you are effectively working for them, it's like you're a poorly paid consultancy” (Gaver, 2020)**. A related aspect of this issue is the specific value-add that Design Research tends to offer e.g., **“stepping outside [of their environment] coming over the threshold into our facilities, meeting some of our people, using some of our toolkits, allows them to re-question what and how they are designing” (Speed, 2020)**. Relationships with businesses and community groups local to academic institutions were cast cited as having potential but with caveats about scale, funding streams, and relevance:

“We're only going to get about £1,000 out of it [but] the actual genuine impact might be that much greater” (Kirman, 2020);

“The councils of course have no money and never have done, but the local enterprise, I've never tried this, but in Southampton if we were doing something like this you'd involve the Port” (Hall, 2020);

“We worked with a local transport company [...] Fantastic local partner, it was good to collaborate with them [...] when they realised that actually because of the position we were in we could offer to do it for free, they eased up on what they wanted us to ask as part of this consultation [...] They were actually really, really excited when they finally got the data, they were like ‘this is amazing, we hadn't thought about these things’. That's led to further work with them.” (Kirk, 2020).

Frequently the role of Design Research is to ask challenging questions and proffer answers which may be uncomfortable or pose quandaries to an existing product or service model. When Design Research is providing a critical lens, and yet the thing which is being critiqued is funding the work, there is an intrinsic conflict of interest which has the potential to become a problem:

“.. there's an implicit sense that it's harder to challenge. It's harder to question. I think you inevitably have to always remember the people that are funding you have got a bottom line and they're funding you probably to help them with that bottom line. There's always an underlying interest in products, service.” (Vines, 2020).

Conversely when the equation is such that a partner is benefitting from the Design Research ‘for free’ (in cash terms) the sanctity of academic research prevails, which in turn actually *increases* the value of the collaboration.

“Trying to develop a relationship with a kind of greater equality where you can actually do the kind of non-commercial research that we find most productive. It is harder if they're funding you directly than if they are providing any other kind of support.” (Gaver, 2020)

While clearly identified as a risk, this issue does not exist across the board, and there are notable examples of healthy and productive cash investment (e.g. Design Informatics and the Advanced Care Research Centre's £20m investment from Legal and General[52]), they are in the minority. Several interviewees noted private funding for doctoral students: **"partners come in and put some money in for PhD students" (Reeves, 2020)** observing that such funding was, in the case of PhDs funded by larger and richer corporations, free from the aforementioned conflicts of interests:

"I was lucky enough to have my PhD funded by Microsoft. But they gave me a completely clean slate. At no point did they say this is getting too critical or negative [but] if it's a smaller institute and their whole livelihood is based on development of a particular technology, then of course they don't want to hear too much negative stuff." (Auger, 2020).

The successful private investments which are cash-based, the funding of doctoral research, and the successful in-kind investments have a common thread among them. It seems that key to making such relationships productive is to ensure that all participants are clear what the value-proposition of Design Research is, and in all of the examples touched upon in the interviews Design Research played a questioning and exploratory role. The skills and knowledge about how to manage this, communicating if effectively, are not formulaic and require a bespoke and personal engagement: **"I don't know how anybody within a University could train other people in a university to be able to work with industry partners. It's a nonsense. I think you have to be out in the world and you have to be working with them, because you couldn't possibly understand otherwise" (Luger, 2020).**

Design Reserach's critical lens is clearly more valuable at a relatively early stage of development processes where the work can facilitate the finding of alternative trajectories at a point when they can realistically be delivered and before assumptions around a given services form or function have become 'baked in'. Design Research's role in demonstrating or creating novel uses of technology for direct exploitation were not evident in our interviews. Rather the successful projects challenged assumptions and explored alternatives. Hence, seeking investment in a similar vein will likely increase the chance of success.

Regardless of whether investment comes through in-kind or cash contributions, there was a clear consensus among interviewees that having non-academic project partners is often a prerequisite for Design Research projects. Moreover, in order to facilitate such collaborations, long-term relationships are essential and require a significant and sustained effort to build and maintain. Through reciprocal trusting relationships profound collaborations can hinge on good Design Research for organisations of all types, from corporate and financial institutions to community and cultural groups. Arguably a key for many centres of excellence for Design Research their ability broker, maintain, and utilise such relationships. Urgo, to accelerate and increase private investment, support should be offered for building collaborative relationships which in turn will facilitate world-class Design Research opportunities.

[52] https://edinburgh-innovations.ed.ac.uk/2020/01/27/20m-lg-partnerhip-launches-acrc/

8. Recommendations

In this concluding section the content of the report is reflected and summarised into succinct recommendations. The intention of the recommendations is to highlight where and how University-led Design Research can best partner with government and industry to create positive economic, cultural and social outcomes for the whole of the UK, around the theme of AI and Data. The recommendations reflect the research approach (see section 2) and are inferred from the interviewees experience, knowledge and opinions. The recommendations are presented concisely according to a consistent structure and include reference to the relevant section(s) of the report.

Recommendation 1 - Disambiguate the Domain

Disambiguate funding calls, published research, and reporting about research, which relates to AI and Data.

Background: The terminology is ambiguous. While an element of ambiguity is unavoidable, the lack of clarity in how the key terms AI (section 3) and Design Research (section 5) are used causes significant problems for the identification and articulation of the value of investment (section 4).

Recommendation 2 - Communicate the Benefit

Create a codification of Design Research's potential utilities and use this to promote and facilitate collaborative relationships.

Background: There is a broad scope of potential benefit for different types of Design Research in different contexts (section 6). Building relationships with collaborators over time is a time-consuming and challenging task (section 7). In order to help to do this a classification or codification of Design Research's key archetypal contributions (section 5) and how they may be applied to the plethora of interpretations of AI (section 3) would be hugely beneficial. This includes making the distinction between research *through* design, research *into* the design industry, and mapping the contribution of doctoral research to the overall landscape.

Recommendation 3 - Unify Investment Strategy

Strategically review UKRI's AI and Data centric Design Research portfolio in order to identify problematic aspects of peer review and assessment processes.

Background: Technology focussed Design Researchers note outward positivity from AHRC which is tempered by less enthusiastic reviews, this is in contrast to EPSRC (and other) funders who are less explicit about promoting Design, but appear to be more supportive in practice (section 4). Unifying approaches, which will begin with understanding and clear communication, will maximise potential co-investment opportunities.

Recommendation 4 - Manage Expectations

Make clear distinctions between product-focused and exploratory investments in Design Research.

Background: The perception that 'Design Research' will *directly* lead to innovative products in the AI and Data domain is not supported by the experience of the interviewees or their project portfolios. Notwithstanding this finding, the commercial, cultural and societal benefit in the of Design Research in the technology domain *is* clear, in particular when for developing alternative, future-focused, and disruptive perspectives (section 6). The interpolation of both aims without prior clarification introduces the potential to undermine valuable collaborative partnerships (section 7).

Recommendation 5 - Evaluate Investment Value

Develop a fitting means to quantify the relative value of in-kind and cash investments in terms of overall research impact's value.

Background: The majority of Design Research in the AI and Data domain *depends* on in-kind contributions from partners, and high quality partnerships can significantly enhance the impact of research in economic, societal and cultural terms (section 7). Conversely, although direct funding is sometimes productive, it can be problematic and provide challenges to the kernel of the approach (section 6). A newly developed approach would provide means to compare and contrast the value of research outcomes in terms of scale and type of investment.

Recommendation 6 - Support Collaboration

Provide funding, advice and support for research institutions to build and maintain investment partnerships with non-academic organisations.

Background: The relationships which research collaborations are built on can take a long time to develop and need to be maintained (section 6). These relationships are an invaluable and crucial asset in co-investment (section 7).

Recommendation 7 - Promote Equity and Diversity

Promote research around AI and Data which strives to ensure innovation helps to dismantle the structural disadvantages endured by the world's minorities rather than galvanise them.

Background: Given the propensity of AI to amplify the biases of the world and the extreme sensitivity around bias, future research should promote an agenda of equality through technical means, promoting a more diverse community of researchers (section 5), and understanding the potential consequences of biased data (section 3).

Recommendation 8 - Support Designing with Data

Support the development of theory and curricula relating to data as a medium for Design.

Background: While the rhetorical force of the term AI is undeniable, data is what allows it to work, and the qualities of data are a key design challenge of our time. Conceptualising how data and Design intersect one another in research, innovation, and education are key issues (section 5). To empower Design Researchers to ask relevant and productive questions, and therefore to leverage it's key strengths, investment should support the development of both the theory and practice of Designing with Data (section 6).

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Appendix 1: Interviewee Profiles

James Auger is a designer, researcher and teacher. Graduating from, and then teaching on the Royal College of Art's influential Design Interactions programme, James has become a highly influential scholar of Speculative Design (2013). Currently affiliated with the École normale supérieure (Paris-Saclay), James has worked on numerous projects related to the space including Blockchain Now and Tomorrow (European Commission[53]) and Beyond the Face (AI profiling with Aberystwyth University[54]).

Anab Jain is the co-founder of design studio Superflux and Full Professor in the Industrial Design Department at the University of the Applied Arts, Vienna. Through their work with Superflux, Anab and co-founder Jon Arden produce world-leading Design Fictions which have helped to define the field and have a high profile. Her work has been exhibited at the Victoria & Albert Museum[55], she has presented at TED[56] and completed work for the United Arab Emirates Ministry of Energy[57].

Chris Speed and Ewa Luger (who were interviewed at the same time) are based at the University of Edinburgh's Design Informatics. Chris is the director of the AHRC-sponsored Creative Informatics cluster. Ewa is a Chancellor's Fellow in Digital Arts and Humanities, consulting researcher for Microsoft Research, a Fellow of the Turing Institute, and a director of the Human Data Interaction Network[58]. They are involved in a wide range of related Design Research initiatives including the flagship AHRC Creative Informatics[59] programme.

Bill Gaver and Andy Boucher (who were interviewed at the same time) are based at Goldsmiths, University of London, where they are co-directors of the Interaction Research Studio. The world-renowned studio has helped to pioneer Design Research approaches, with a particular focus on Research through Design. Their design-led work has been utilising and critiquing our relationships with data and computation for over 15 years through projects such as Datacatcher[60], Photostroller[61] and Local Barometer[62].

Ann Light is a Professor of Design and Creative Technology at the University of Sussex. Her work uses Design-led approaches to critique Human-Computer Interaction and technology more broadly. She has a strong track record of securing research from AHRC, as well as EPSRC and EU fundings. Current projects include the H2020 project Creative Practices for Transformational Futures (CreaTures)[63].

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[53] https://publications.jrc.ec.europa.eu/repository/bitstream/JRC117255/blockchain_online.pdf
[54] https://www.aber.ac.uk/en/news/archive/2010/03/title-83161-en.html
[55] https://www.vam.ac.uk/blog/digital/the-future-starts-here-an-interview-with-design-studio-superflux
[56] https://www.ted.com/talks/anab_jain_why_we_need_to_imagine_different_futures
[57] https://superflux.in/index.php/work/futureenergylab/#
[58] https://hdi-network.org
[59] https://creativeinformatics.org/
[60] https://goldsmithsdesignblog.com/2015/05/28/interaction-research-studio-launched-datacatcher-book-and-film/
[61] http://research.gold.ac.uk/4588/
[62] https://research.gold.ac.uk/5523/1/Local_Barometer.pdf
[63] https://cordis.europa.eu/project/id/870759

Alison Powell is an ethnographer and social scientist based at the London School of Economics. In her work she utilises practice-based approaches to research issues pertaining to ethics and computing. Currently she is lead on the AHRC-funded JUST AI Network (in collaboration with the Ada Lovelace institute)[64].

Stuart Reeves is a member of the Mixed Reality Lab and Horizon Digital Economy Research Institute at Nottingham University. He has published widely on issues relating to Design, Data and Human-Computer Interaction more broadly. His funded projects include the From Data to Human Experience[65] and his EPSRC fellowship exploring the links between academic and industrial User-Experience Design[66].

Dave Kirk is a Professor in Human-Computer Interaction and the director of Newcastle University's Open Lab where his research takes a particular interest in Design Research methods. Through his career he has transitioned from an experimental scientist to exploratory design research. He is the Principal Investigator on several significant and relevant projects including the Digital Economy Research Centre[67], the Centre for Doctoral Training in Digital Civics[68], and the Centre for Digital Citizens.

Ben Kirman is a creative technology and game designer, who is currently a Lecturer in Interactive Media at the University of York and member of Digital Creativity Labs. His research leverages design via fiction, criticality and games to create unusual interactive experiences to unpack potential futures, understand modes of interaction. His current research portfolio includes a wide range of projects including an Industrial Strategy Challenge Fund Audience of the Future Demonstrator (WEAVR: Immersive Cross-Reality Experiences)[69], a collaboration with an international e-sports company, and through to collaborations with local community theatres.

Dame Wendy Hall is a computer scientist who has recently been appointed as Chair of the Ada Lovelace Institute, is Executive Director of the Web Science Trust, and co-authored the UK Government report on Growing AI in the UK[70].

Shannon Vallor is a philosopher of technology and is the Baillie Gifford Chair in the Ethics of Data and Artificial Intelligence at the Edinburgh Futures Institute at the University of Edinburgh. She was formerly a Visiting Research and Ethicist at Google and is author of the forthcoming book Lessons from the AI Mirror: Rebuilding Our Humanity in an Age of Machine Thinking.

John Vines is Professor at Northumbria School of Design. His research uses design methods to explore how people experience, appropriate, and use digital technologies as well

[64] https://www.adalovelaceinstitute.org/our-work/just-ai/
[65] https://gow.epsrc.ukri.org/NGBOViewGrant.aspx?GrantRef=EP/M02315X/1
[66] http://www.cs.nott.ac.uk/~pszsr/#fellowship
[67] https://gtr.ukri.org/project/E7A58D37-F67E-452D-A68F-55579A67CBB4
[68] https://digitalcivics.io/
[69]
https://digitalcreativity.ac.uk/news/dc-labs-and-university-york-announced-major-stakeholder-%C2%A358m-rd-project-immersive-audience
[70] https://www.gov.uk/government/publications/growing-the-artificial-intelligence-industry-in-the-uk

as focusing on the ethical and methodological aspects of Design Research. In addition to research examining issues such as social isolation among carers, intergenerational conversations about dementia, measuring charitable outcomes, and community decision making he has worked on projects including Playing Out with the IoT[71], Ox-chain[72] and is a Co-Investigator on the Digital Economy Research Centre[73].

Julian Bleecker and Nicolas Nova (who were interviewed at the same time) are co-founders of the renowned agency Near Future Laboratory[74], pioneers of the Design Fiction field. Julian holds a PhD in History of Consciousness, was formerly an Interaction Designer at Nokia Labs, and runs cycling technology startup Omata. Nicolas holds two PhDs in Social Sciences and Human-Computer Interaction, he is an Associate Professor at Geneva School of Art and Design, associate researcher at SciencesPo medialab (Paris), and frequently presents his research about the intersection between society and technology to global audiences.

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[71] https://gow.epsrc.ukri.org/NGBOViewGrant.aspx?GrantRef=EP/P025544/2
[72] https://gow.epsrc.ukri.org/NGBOViewGrant.aspx?GrantRef=EP/N028198/1
[73] https://gtr.ukri.org/project/E7A58D37-F67E-452D-A68F-55579A67CBB4
[74] http://nearfuturelaboratory.com/

Appendix 2: Interview Schedule

The interviews were semi-structured around the following schedule. Not all questions were asked of all interviewees, as some were not relevant in all contexts, e.g., questions relating to REF not relevant to non-academics and questions relating to UKRI funding not relevant to international interviewees.

- What do you think is meant by the terms ‘AI’ and ‘Data’, how are they related?
- What is the relationship between ‘Design’ and ‘Research’?
- What role does Design play in AI & Data research projects, for example does it aid creativity, provide a critical lens, help encourage interdisciplinarity, or something else?
- Do you work with non-University partners (e.g. private sector, NGOs, and charities) on AI & Data research projects?
- How does Design Research benefit your partners and do they fund University-based research directly?
- Who (else) funds your Research work/time? (e.g. AHRC, EPSRC, others)
- Do your partners contribute cash or in-kind match funding?
- What REF panel do you submit your work to?
- Do the Designers in your AI & Data projects tend to work alone, act as linchpins in the team, or somewhere in between?
- How does Design help make your AI & Data research more impactful?
- What precedents from history do you refer to in order to argue for the value of Design in AI & Data research?
- What disciplinary backgrounds do Designers researching AI & Data have, and what skills or training will future designers need?
- Why is Design important for AI & Data research?

Appendix 3: Accuracy in AI Systems

Accuracy is often expressed statistically, for example, if an AI system is used to classify emails as spam, a simple accuracy measure would be the number of emails correctly identified as spam as a proportion of all the emails. However such a measure could be problematic. For instance, if 90% of all emails are spam, then you could correctly achieve 90% accuracy by simply labelling all emails as spam. For this reason, alternative measures are used to assess a systems performance, which reflect the balance between two different kinds of errors[75]:

A ***false positive*** is when an AI system incorrectly labels as positive (eg emails classified as spam, when they are genuine)

A ***false negative*** is when an AI system incorrectly labels as negative when they are actually positive (e.g. emails classified as genuine, when they are actually spam).

The balance between these two types of errors can be captured through various measures, including:

Precision: the percentage of cases identified as positive that are in fact positive. For instance, if 9 out of 10 emails that are classified as spam are actually spam, the precision is 90%.

Sensitivity: the percentage of all cases that are in fact positive that are identified as such. For instance, if 10 out of 100 emails are actually spam, but the AI system only identifies seven of them, then its sensitivity is 70%.

There are trade-offs between precision and sensitivity. If you place more importance on finding as many of the positive cases as possible (maximising sensitivity), this may come at the cost of some false positives (lowering precision). Thus the performance of an AI system is very much in the hands of its designer.

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75 https://ico.org.uk/about-the-ico/news-and-events/ai-blog-accuracy-of-ai-system-outputs-and-performance-measures/