Datafication, Dehumanisation and Participatory Development

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Abstract: This paper asks whether datafication practices are dehumanising international development and if a human-centred and participatory datafication is possible. The paper uses Habermas' theory of the different 'knowledge interests' that constitute different forms of social action. Three kinds of datafication projects are explored: humanitarian AI, digital-ID and community mapping. The authors argue that data-science and participatory practices are forms of social action that are shaped by different knowledge-interests. It is argued that the technical knowledge interests shaping datafication projects conflict with high-level policy commitments to participatory development. Ethical Principles of AI are assessed as a route to more human-centred practices of datafication for development. The authors argue that avoiding tokenistic forms of participation will require the incorporation of practical and emancipatory knowledge interests and the use of new monitoring and evaluation tools to trace the achieved levels of participation of different actors at each stage of the project cycle.

Keywords: Datafication, participation, dehumanisation, human-centred, artificial intelligence, critical theory

1. Introduction

Datafication is transforming the landscape of international development. Datafication of development refers to the increased use of digital data in development knowledge production and decision-making processes [1]. The algorithmic processing of big data using artificial intelligence is impacting multiple areas of development practice [2]. Development agencies have been under significant pressure from funders to demonstrate innovation in the datafication of development [3, 4]. Humanitarian agencies have been under similar pressure to innovate using data from satellite imaging, remote sensing, biometric identification, social media, and other data sources to inform operational decision-making [5, 6]. The pressure to make digital data central to decision-making is reflected in a range of high-level policy commitments including the Digital Development Principle[1] to *"be data driven"*. As a result, development agencies are active in supporting states in the datafication of areas including identification (digital-ID), border control, social protection, online government services, and predictive analytics [7, 8]. These data-centred innovations have delivered significant efficiencies and development benefits as well as introducing new risks and challenges. This paper is focused on whether this turn to data-centred development necessarily comes at the expense of existing commitments to human-centred development, and assesses the potential for synergy between the two approaches using participatory practices.

Prior to digitalisation, a citizen might seek development assistance via a face-to-face meeting with a government officer, an agricultural extension worker, or a community meeting. Participatory development aims to enhance the agency of marginalised people to take part in development decision-making that affects their lives through human-centred processes of dialogue and critical reflection [9, 10]. Some datafication processes explicitly aim to 'disintermediate' development processes by removing human intermediaries and the need for face-to-face human dialogue and interaction [11]. We argue that such processes can dehumanise the development process, making it more data-centred than human-centred and less participatory [8, 6]. We examine evidence that such processes of datafication disproportionately increase the agency and power of external actors and private corporations with the unintended consequence of widening inequality, reproducing unequal power relationships, and leaving behind the most marginalized [7, 12, 13, 14, 15].

Information systems development has predominantly been considered as the application of the scientific method to increase efficiency and efficacy [16]. Walsham [17] was influential in popularising the use of interpretive theory as a lens to understand information and communication technology for development. There has been less use of critical theory to analyse digital development (see however [18, 19, 20]. This paper contributes to the later scholarship by combining Habermas' [21] critical theory from the Frankfurt School with critical participatory praxis from the global South.

Section 2 outlines Habermas' critical theory of knowledge interests and social action to argue that data science is shaped by the desire to predict and control. Section 3 reviews the impact of datafication in international development and the claim that it leads to dehumanization, exclusions, and widening power inequalities. Section 4 reviews the emergence of proposed new ethical principles for AI in international development and assesses them against critical theories of participatory development. Section 5 assesses whether participatory datafication is possible and whether new ethical principles can produce a more human-centred datafication in international development. Section 7 concludes that if marginalised people are to play a decision-making role in development projects affecting their lives then more practical

[1] The Digital Development Principles were developed by funders, multi-laterals and international development agencies to guide the use of digital technologies in development. https://digitalprinciples.org/

and emancipatory knowledge interests are required alongside new practical tools to guide participation planning and evaluation in datafication projects.

2. A Habermasian Perspective on Data-centred Development

This section introduces Habermas' critical theory of social action and his typology of knowledge interests as a theoretical foundation to examine the datafication of international development.

2.1. The Critical Theory of Habermas

A fundamental issue in digital development is which interests are prioritised and who benefits. This paper explores which interests are prioritised in data-centred approaches to international development. We draw on Habermas' critical theory of social action to illuminate these issues.

Habermas argues that the social action of humans is always constituted by what he called knowledge interests. In his book Knowledge and Human Interests, Habermas [21] (1972) claims that there are three kinds of fundamental human interests that determine three paradigms of knowledge production*: technical, practical and emancipatory*, as illustrated in Table 1. According to this perspective, the human desire to explain, control and predict constitutes the 'technical' knowledge interest that is characteristic of positivist empirical-analytical processes in the natural sciences. The human desire to understand meaning and to communicate constitutes the 'practical' knowledge interest that is characteristic of the interpretivist hermeneutical processes in the humanities. And for Habermas, the human desire to be free from domination constitutes the third category of 'emancipatory' knowledge interests that are characteristic of the critical social sciences. While these are ideal types that are not mutually exclusive, the categories are analytically useful.

Lyytinen and Klein [16] in their analysis of Habermas' critical theory show how the technical knowledge interest serves 'purposive-rational' social action based on empirical science that follows technical rules to maximise efficiency and achieve specific goals. In comparison, practical knowledge interest serves communicative social action to achieve mutual understanding, with an emphasis on common understanding of norms, meaning, values and maintaining social relationships. Achieving agreement through communicative action entails discursive processes that enable the assessment of the truth of statements, sincerity of speech and validity of claims. Emancipatory knowledge interests by comparison use social dialogue to critique the abuse of power; produce knowledge about the causes of social injustice, and guide social action to overcome it. Lyytinen and Klein [16] see the third category as uniting the other two knowledge interests with enquiries that use critical reflection to critique power inequality in order to inform social action to improve equity. Although analytically distinctive, in practice one approach often draws upon methods from the other: for example when critical-emancipatory approaches use discursive communicative action to investigate the validity of knowledge claims and truth statements.

Knowledge Interest	**Social Action**	**Mediating Elements**	**Sciences**	**Purpose**	**Process**
technical	purposive-rational	work systems	empirical-analytic	explanation, prediction, control	scientific method, verification
practical	commun-icative action	cultural institutions, natural language	historical-hermeneutic Geisten-wissen-schaften	understanding of meaning, expansion of inter-subjectivity	ideographic method, dialogue rules of hermeneutics
emancipatory	discursive action	power unwarranted constraints	critical sciences, psycho-analysis, philosophy	emancipation, rational consensus, Mundgkeit	reflective method criticism of assumptions

Table 1. Aspects of Knowledge Interests. Source: [16]

2.2. Epistemological Underpinnings of Datafication in Development

Applying Habermas' critical theory, we can examine which knowledge interests and social actions are served in the processes of datafication and AI application, and what are the implications for international development.

One of the attractions of data-driven development is the impression of scientific neutrality and precision provided by computing data with algorithms to produce what appear to be 'objective' truths. Epistemologically, data-centric development is often premised on big data as the source of knowledge for decision-making in development [4, 22, 23, 24]. Flyverbom et al. [25 p.39] point out that big data "creates a different ground for the evaluation of 'truth'" in international development, by making knowledge claims on the basis of the large quantity of data, especially when they are real-time data. This also gives rise to the tendency of focusing on correlation rather than causation, which is increasingly used for decision-making.

This approach was evidenced when Hernandez and Roberts [8] reviewed 49 projects using predictive analytics in humanitarian work. Predictive analytics uses a form of artificial intelligence called machine learning to operate on big data sets using statistical modelling to make predictions about the probability of future events (ibid). It is used to support decision-making in humanitarian responses to drought and mass population displacements, to inform the allocation of staff and the management of supply chains. Predictive analytics is also used to inform social protection entitlements, employment decisions, policing and criminal justice, and governance decision-making [26, 27, 28, 29]. Apart from humanitarian agencies the next most common actor in humanitarian predictive analysis projects was private corporations including Microsoft, Google and the global association of mobile phone companies GSMA [8]. Some concerns have been raised about the increasing role of private corporations in datafication for development and the accompanying shift in power away from disadvantaged people [7]. Privacy International [30] raised serious concerns about the World Food Programme sharing its humanitarian data with private sector data partner Palantir and court cases are pending regarding the role of Facebook data in the Rohinga genocide [31].

It is clear that a rule-bound technical rationality is employed in data-centred development that seeks to optimise efficiency, control and predictability in ways that echo Habermas' first category. The efficient calculation and allocation of human and material resources are no doubt important aspects of international development. While datafication and AI may serve instrumental and strategic purposes in international development, e.g. increasing managerial efficiency and fulfilling strategic objectives of power holders, it is important to recognise that the knowledge created through datafication and machine learning does not necessarily corresponding to any 'objective truth'. The assumption that big data is better than localised, situated, and contextualised 'thick data' is highly problematic. First of all, the term 'raw data' is an oxymoron as data is always already 'cooked' [32, 33]. As Manovich [34 p.224) puts it, "Data does not just exist – it has to be generated". Data is generated by selectively subtracting from reality, a reductive process resulting in binary ones and zeros. In the sociology of knowledge, it has long been recognised that scientific facts are products of a series of human choices in categorisation, labelling, and measurement, produced in contested processes [35]. As a result, data is always partial, biased, and political. Similarly, machine learning is not neutral, it inherits the ontology, bias, and politics already baked into the data sets on which it relies.

Furthermore, through the extraction and decontextualisation of big data, data-centred development inevitably marginalises *practical knowledge* grounded in the shared understanding of local norms and social relations which have been proven to be imperative in the sustainability and inclusiveness of development projects. This practical knowledge and the human ability to interpret it contextually, is subtracted when big data is collected and fed into machine learning processes. Furthermore, datafication and algorithms that are effectively black-boxed are not transparent or accountable to human questioning; this inevitably diminishes emancipatory knowledge interests' ability to challenge any unwarranted abuse of power. The opacity and the lack of accountability of datafication and algorithmic processes substantially undermines the agency of local participants to: verify the knowledge claims put forward by datafication decision making; examine the underlying power relations; or participate in the knowledge creation and decision-making process; principles which are essential to human-centred development. While machine learning has an emphasis on automated pattern recognition, participatory methods involve disadvantaged people in dialogue designed to uncover the distinct root causes of their disadvantage and overcome it together.

The data-driven development approach is a significant departure from the ideals of participatory human-centred development in which marginalised people are the source of knowledge, and in which participatory dialogic processes are the means and ends of development. The requirement for computational power and data analytics skill means that the process of development knowledge production is not carried out locally by marginalised and disadvantaged people themselves and as a result they can be left without agency and none the wiser. In other words, development decision-making processes are often dehumanised and physically removed from the relevant human contexts, prioritising automated algorithmic analysis of big data over in-depth deliberative, contextualised and participation-based knowledge production [36]. It should be noted that this shift of knowledge paradigm in international development is also likely to lead to the replacement of local expertise, and intermediary issue experts, shifting power relations in the field of international development [7, 25]. As we discuss later the reduced participation of local people and intermediaries in digitalisation processes in often accompanied by the increased participation of external private companies who partner in the extraction of data and its processing.

For this reason, the idea that development should *"be data-driven"* as stated in the Digital Development Principals needs to be problematised, both because data may be gender or racially biased and because marginalised people have the right to voice their opinion and be at the centre of any decision-making about their lives [9, 37]. Although the Digital Development Principals also say *"design with users"*, we argue that it is not only 'users' who have the right to participation, and that the right to participation extends beyond the design stage of development projects.

In the next section, we will review the shift from people-centred to data-centred development, and look at specific examples of datafication and their implications for development.

3. The Impact of Datafication on International Development

Datafication has occurred in multiple sectors of international development. Examples include the digitalisation of microfinance [38], digital governance [39], digital identity [40] and digital social protection 41]. Increasingly, access to healthcare, employment, criminal justice, and decisions about resource deployment are made on the basis of automated analysis of big data sets using artificial intelligence [36, 8].

In the rest of the section we examine the impact of datafication on international development.

3.1. Dehumanisation of Development Process

Datafication often delivers valued benefits of cost reduction, efficiencies that improve speed of service delivery, convenience to citizens and reduction in corruption. However, datafication also brings the risk that local contextual knowledge and expertise is disintermediated. Sharma and Joshi [42] argue that digital development processes tend to design out local knowledge of development settings provided by those with lived experience and the ability to make a situated assessment of development processes.

When human-centred development processes are replaced by data-centred processes the effect is dehumanising. Dialogue and human interaction are replaced by computer-mediated machine calculation. Instead of convening a village meeting or conducting worshops, extracted data can be used to generate algorithmic decision-making. Funders are incentivising development agencies to experiment with satellite data, remote sensing, social media data and artificial intelligence. Although it is often argued rhetorically that the two methods should be complementary, in practice the funding disproportionately incentivises datafication rather than participation. Research from the United Nations has noted that datafication projects are tending to replace, rather than complement, analogue access. As pointed out in a UN special report on extreme poverty and human rights, "[t]he digital welfare state sometimes gives beneficiaries the option to go digital or continue using more traditional techniques. But in reality, policies such as 'digital by default' or 'digital by choice' are usually transformed into 'digital only' in practice" [43, p.13].

The research in 49 predictive analytics projects by humanitarian agencies [8] examined how historic data of previous humanitarian emergencies is being combined with data from sources including mobile phone records, social media, satellite images, and meteorological data to create the large datasets needed to predict refugee movement, food security, and inform aid deployment. The researchers noted the risks associated with reliance on repurposed datasets containing omissions and biases that lead to algorithms reproducing past errors, prejudices and inequalities (ibid).

McQuillan [44] argues that machine learning is a particular form of knowledge production native to big data. He acknowledges that the technology itself is not inherently good or bad, nor is it inevitable that its use will cause harm. However, he argues that the affordances of machine learning, the ability to recognise patterns in historic data with predictive power, abstracts from human social and political contexts in ways that *"invisibly distorts the distribution of benefits and harm"*. The opacity of machine learning decision-making can cause or obscure harm. The basis on which predictions are made are unknown, as are the gender, race or class biases hidden in the data. This method of opaque knowledge production obstructs people's rights to transparency, participation, and accountability. McQuillan warns that the use of machine learning risks adopting a drone-like perspective on society; a perspective that combines a top-down view of society leading to harmful interventions of dubious legality.

It is thus a serious concern that reliance on big data and automated decision-making has the effect of de-centring the human agency of affected populations and of experienced frontline practitioners and replacing it with the mechanical logic of algorithms. The humanitarian principle to "*keep people at the centre of everything we do*" [6] is at risk by the encroachment of artificial intelligence at the behest of funders and powerful commercial interests. It is therefore imperative to keep humans in the loop to ensure development agencies remain accountable to the populations they exist to serve (ibid).

3.2. The Exclusion of the Vulnerable

Datafication has become an important means of managing population identification systems (Digital-ID). Digital-ID systems are increasingly used a gateway to control social protection systems worldwide, including (un)conditional cash transfers [43, 41]. Access to digital welfare payments is often used to motivate for the creation of identification registries by humanitarian agencies and states. Digital-ID systems increasingly use biometric identification such as fingerprints, iris-scanning or facial recognition [45, 46].

Entitlement to welfare entitlements for refugees, pensioners or mothers is increasingly algorithmically determined and cash is often transferred directly to people's mobile phones, or electronic debit cards. This datafication of affected populations makes them machine readable and machine processable – a significant efficiency gain for humanitarian or state agencies but also another form of dehumanisation compared to the person-centred processes that are replaced. The move to digitalisation of identification is often achieved in partnership with private corporations, raising issues of data ownership, privacy and protection [7, 41]. Global financial corporations and the world's largest data aggregators are partnering with humanitarian organisations in humanitarian datafication projects including Mastercard[2], Goldman Sachs[3] and Experian[4] .

The Aadhaar digital-ID system in India is the world's largest digital-ID system. It is the model for many other national identification systems and the subject of a great deal of research including dedicated special journal issues [47]. Digitalised biometric data is recorded about each citizen enabling them to access multiple entitlements and services (Gov of India, n.d.). The Aadhaar ID has become a requirement to access a wide range of welfare services and social protection entitlements and has delivered valuable benefits of convenience and service access to many millions of citizens. However, research shows that the most marginalised citizens are excluded by the systems and as a result suffer deprivations. When visiting ration shops citizens must authenticate biometrically but the system regularly fails as a result of connectivity issues or because of worn fingerprints. Chaudhuri [48] documents how shop owners manipulate the Aadhaar system to make it work, revealing a paradox of (dis)intermediation; although the system is designed to obviate the need for human mediation the systems regularly do not function without the creative improvisation of intermediaries who break the rules and modify the system to secure the intended development outcome. Ironically, Chaudhuri finds that a process of datafication created to design out human errors and corruption only works in practice when humans design out the technology errors to ensure disadvantaged citizens have access to rations (ibid).

3.3. Shifting Power Relations in Development

Datafication is also shifting power and agency away from traditional actors in ways that increase the power and agency of technology corporations [7]. This happens as a result of private-public partnerships that are employed to digitalise government functions and development agency operations. The increased use of commercially owned big data and proprietary algorithms has the effect of making citizens increasingly visible to corporate and government actors resulting in a shift of power to those who hold the most data (ibid.).

In their analysis of datafication Heeks and Shakhar [15] use a data justice lens to assess who benefits from a range of community data mapping initiatives in Kenya, Indonesia, and India. Their analysis found that target communities experienced real incremental benefits, but that external actors and wealthier communities gained the most. Data about the most marginalised communities was not captured at all and the most significant social justice issues were made invisible by the datafication process with the effect that overall, there was an increase in relative inequality. Heeks and Shakhar used an information value chain framework that traces the steps by which data is captured and transformed into developmental results. Among their conclusions is the finding that *"In general, then, these pro-equity data initiatives were somewhat 'extractive' in utilising a few community residents as data sources but largely excluding them from all other information value chain processes"* (ibid).

Commercial datasets and proprietary algorithms have been criticised for being black-boxed technologies [49] not open to public scrutiny, and therefore raising issues of transparency and accountability for development processes. Marginalised communities cannot participate meaningfully in development initiatives that affect their lives if the data and decision-making processes that shape them are opaque or regarded as proprietary trade secrets. Studies have shown that big data reflects historical patterns of prejudice and disadvantage along intersecting lines of gender, race and class leading to the finding that use of artificial intelligence often reflects, reproduces, and amplifies historical patterns of (dis)advantage [12, 50, 14]. Where datasets and/or algorithms are not open to public scrutiny there is no transparency, no accountability mechanism, and no route to redress [51, 12, 50]. As a result, human rights groups have actively campaigned against the deployment of facial recognition, predictive policing and smart city technologies that rely on these technologies [52, 53]. Some development agencies including Oxfam UK imposed moratoria and some cities have banned the technologies [54].

In short, datafication delivers clear benefits including efficiency, convenience and expanded service access. Nevertheless, the centralisation of technical knowledge and the domination of techno-rationality take place at the expense of practical knowledge, resulting in the dehumanisation of development processes; and actively suppress

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[2] Mastercard Transforming Humanitarian Response https://www.mastercard.us/en-us/business/governments/find-solutions/humanitarian-aid.html

[3] IrisGuard funded by Goldman Sachs https://www.irisguard.com/who-we-are/about-us/

[4] Experian partners with Humanitarian Open StreetMap https://www.experianplc.com/media/4224/experian-sb-report-2021.pdf

emancipatory knowledge interests, as exemplified in the exclusion and exploitation of the most vulnerable groups in society, instrumentalised through the extraction of data by corporate and government agencies.

4. Return to Human-Centred Development

To address these issues, i.e. to re-enact practical and emancipatory knowledge interests in datafication and AI in development, a participatory approach is imperative.

4.1. Beyond Ethical AI

In respons to criticism of bias and lack of accountability in datafication there has been a proliferation of initiatives to develop ethical frameworks to secure the continued use of artificial intelligence in international development. The Montreal Declaration on Responsible AI[5], OECD Principles on Artificial Intelligence[6] and the UNESCO Recommendation on AI[7] are examples of the many recent initiatives in this space. Floridi and Cowls [55] have conducted meta-analysis to distil the growing number of ethical principles into a 'Unified Framework of AI Principles in Society'. The Montreal Declaration on Responsible AI refers frequently to the importance of participation in AI processes. The OECD Principles do not mention participation but they do refer to human-centred values, although there is little detail about how human-centred AI might be realised in practice. Floridi and Cowls [55] note with concern that the various principles that they studied were either global in scope or address western liberal democracies and that perspectives from Africa and Asia are generally unrepresented or under-represented in the current principles.

As Birhane [56] argues in her paper on algorithmic justice, studies addressing the harm caused by artificial intelligence, predominantly (1) revolve around technical solutions and (2) do not sufficiently centre impacted communities. Birhane argues that it is necessary for practitioners to decentre technical solutions such as fixing the data or algorithms. She proposes a fundamental epistemological shift—from rational to relational approaches— and calls for an approach to ethics that goes above and beyond technical solutions. Her proposal envisages that a more human-centred approach is required with relational processes, involving dialogue and critical reflection with affected populations, as opposed to technical "solutions". Similarly, McQuillan [44] proposes a shift away from opaque and dehumanised machine calculation towards a human-centred process of critical reflection and social dialogue in the form of people's councils for ethical machine learning.

On this basis, in the rest of the section, we will argue for the imperative to return to human-centred participatory development with the aim of overcoming the dehumanising effects of data-centric approaches. We start with a critical review of participatory development and discuss how to move beyond tokenistic practices of participation.

4.2. Participatory Development

Participatory approaches to development emerged from a variety of sources in the 1970s onwards [57, 58]. Scholars from the global South including Freire [58], Fals-Borda [59], and Sen [37] argued for a human-centred model of participatory development that enhanced the agency and control of previously marginalised and disadvantaged people. Swantz [60] and Chambers [61] were among those who popularised these participatory models of development which revolve around group dialogic processes. Participatory approaches aim to to engage people with lived experience of poverty and injustice in reflection about their experience of injustice, its root causes, and collective action to overcome it. Participatory practices of development aimed to increase the decision-making role that disadvantaged people play in defining the development initiatives designed to improve their lives. When Amartya Sen embraced participatory development, he stated [37, p.281] that central to his approach to development was *"the idea of the public as an active participant in change, rather than as a passive and docile recipient of instructions or of dispensed assistance"*. This participatory approach to development is consciously human-centred, arguing that the people most directly affected by social deprivations and disadvantage should play a central role in determining how disadvantage and injustice is mitigated and overcome [58, 59, 61, 37, 62].

In addition to this normative and rights-based case for human-centred development there is also an instrumental argument that participation simply produces better development outcomes [63]. This more pragmatic case for people-centred development argues that this is for two reasons, (a) people with the most lived-experience of a development challenge are well-placed to inform the design of solutions, and (b) active community engagement in early stages of the project cycles can be effective in securing uptake and dissemination [64]. From a gender perspective, scholars have evidenced that women's participation in digital development programmes expands their applicability and development impact [65, 66]. In their study of 121 rural water projects, Ishamn, Naravan, and Pritchett [67] found strong evidence that increasing the representation of intended beneficiaries directly improved project outcomes.

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[5] The Montreal Declaration on Responsible AI

[6] OECD Principles on Artificial Intelligence

[7] The UNESCO Recommendation on AI

From the 1980s onwards, the dominant development paradigm began embracing and incorporating aspects of this heterodox participatory approach within mainstream approaches to development [68]. Article 2 of the United Nations [69] Right to Development states that

> *"the human person is the central subject of development and should be the active participant and beneficiary of the right to development"* and that interventions should enable *"their active, free and meaningful participation in development and in the fair distribution of the benefits resulting therefrom".*

By 2015 states and international development agencies unanimously committed themselves to the Sustainable Development Goals (SDGs) including target 16.7: to *"ensure responsive, inclusive, participatory and representative decision-making at all levels"* [70].

The consensus that more inclusive processes produce improved development outputs is reflected in the inclusion of "design with the user" as one of the Digital Development Principles endorsed by funders and international development organisations[8]. It is important however, that participatory development is not confused with 'inclusion'. Participation goes significantly beyond counting the number of people a particular demographic group that are represented in a process. From the outset participation is centrally concerned with the degree of agency and control that participants have in decision-making processes at all stages of the project cycle. The participatory development literature eschews tokenistic participatory process where marginalised people are simply sources of data extraction in the design stage or during the data collection phase but are excluded from other key stages such as project conception, implementation, or evaluation.

From the outset Arnstein [57] argued that in practice it was important to distinguish between 'levels' of participation, ranging from shallow and tokenistic forms of inclusion graduating in normative value up to genuine partnerships in which participants had meaningful decision-making control over development projects that affect their lives. Based on Arnstein's work, many versions of 'ladders of participation' were developed to reflect different operational contexts (Figure 1.)

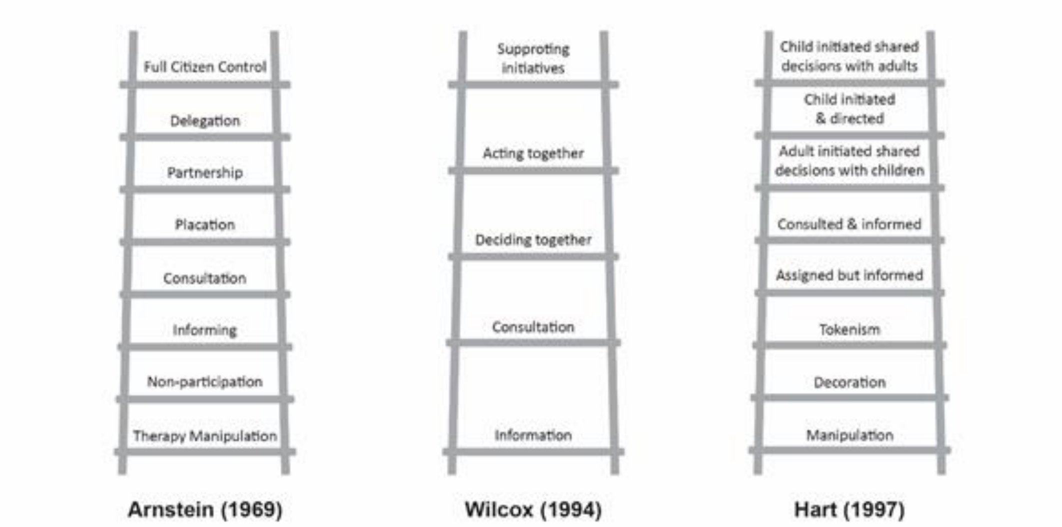

Figure 1. Ladders of Participation. Source [76].

Cornwall and Jewkes [71] argued that what distinguishes valuable participation is the extent to which decision-making power is shifted from external experts to local participants. After the turn of the millennium, scholars conducted a sustained critique of the 'tyranny' of shallow and tokenistic forms of participation in which participants had little meaningful influence over project conception, implementation or evaluation [72, 10]. Hickey and Mohan [62] were among those who argued that in order to move from tyrannical to transformative forms of participation it is necessary to increase the agency and decision-making power of marginalised actors themselves in the design, planning and evaluation of development projects.

Although participatory development theory is well established, and a global consensus on its merits is reflected in its explicit inclusion in global development goals, funding and practice have always lagged significantly behind theory. It is much harder to achieve equitable participation than it is to sign up to it in principle. These criticisms apply as much to digital development projects as in other areas. For example, in their evaluation of four digital mapping projects, Heeks and Shakhar [15] concluded that despite their achievements, the projects were largely extractive with community members entirely excluded from most stages of the project cycle.

[8] https://digitalprinciples.org/endorse/endorsers/

Recognising the value of participation and human-centred development, some of the recent initiatives to re-orient datafication for development initiatives explicitly include increasing participation among their principles. The UNESCO Recommendations on Ethical AI speak most directly to the importance of participation in international development stating that *"Participation of different stakeholders throughout the AI system life cycle is necessary for inclusive approaches to AI governance, enabling the benefits to be shared by all, and to contribute to sustainable development"*. Although *"designing with the user"* is a component of the previously mentioned Principles for Digital Development, what is distinctive about the UNESCO Recommendation is the insistence on participation not only in the design stage but in all stages of the AI system life cycle. The UNESCO Recommendation is also distinctive in noting the importance of considering which stakeholders should be participants in AI decision-making, stating that *"stakeholders include, but are not limited to, governments ... human rights institutions and equality bodies, anti-discrimination monitoring bodies, and groups for youth and children"*.

Participation scholars have argued that it is important to evaluate participation along three dimensions: (i) who gets to participate [9, 73]; (ii) at which stages in the development process [74, 75]; and (iii) with what level of control over the process [57, 10]. Despite agreement in theory, systematic evaluation of along these three dimensions are rare in the research literature. To address this gap, Roberts [76] developed the participation cube to help practioners visualise, calibrate, and structure a three-dimensional analysis of (a) who gets to participate, (b) at which stages of a project, and (c) with what level of control. Figure 2 illustrates 'participation tracing': a practice of tracing the level of participation achieved by different project participants at key stages in the project life-cycle [77].

The vertical axis is calibrated in levels of control achieved over the decision-making process, following Arnstein's 'ladder of participation'. The horizontal axis reflects the different stages in the project cycle. Then a unique trace is made to reflect the participation of each different project actor in each project stage. Figure 2 reflects a retrospective analysis made of participation levels in a specific project in Zambia [77], however the number of stages, the names of participation levels, and participant actors need to be re-calibrated for each new project to reflect that particular context. This kind of participation tracing can be used as either a planning, monitoring or evaluation tool, to assess the levels of participation of different actors and inform the modification and improvement of project processes. To support the move from principles to measurable practices of participatory digital development more research is necessary to develop tools and methods of participatory planning, monitoring and evaluation.

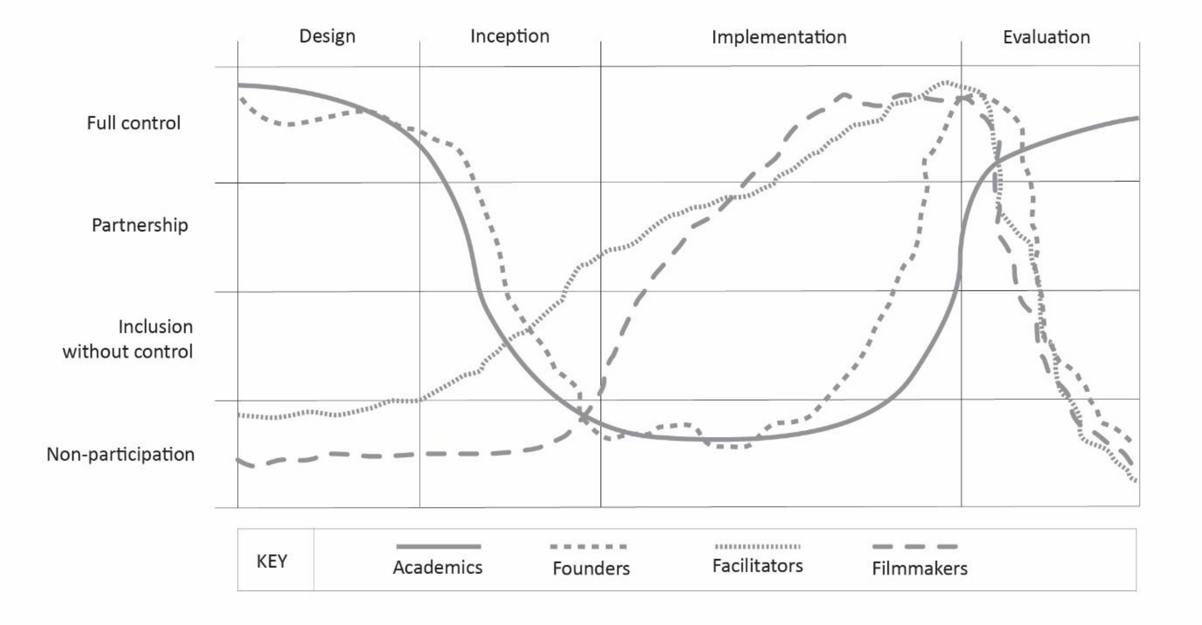

Figure 2. Participation Tracing. Source [77].

5. Discussion

This paper began by framing the discussion of datafication in the context of Habermas' theory of social action and knowledge interests. The evidence shows that data-science and participatory practices are distinct forms of social action that are shaped by different knowledge interests. The shift in priorities of funders, governments and international development towards the datafication of development has involved introducing new actors and new interests. This has had the unintended consequence of dehumanising the datafication of development in three areas: the use of predictive analytics in humanitarian settings, digital-ID programmes, and community mapping projects.

In the case of humanitarian predictive analytics the knowledge interests of control, prediction, and explanation are clear. What Habermas calls our technical knowledge interest for explanation, control, and prediction is understandable in the face of a disaster, as is the desire to use remote sensing and statistical analysis to provide situational analysis in settings where putting 'boots on the ground' may be dangerous or impossible. However, this form of knowledge production appeals to a particular mindset in and outside of emergency settings. Predictive analytics are also being applied by humanitarian agencies in human resource management, water purification, and supply chain logistics. None of the 49 examples of predictive analytics studied involved the participation of affected populations in decision-making roles across different stages of the project cycle. These datafication processes contributed to dehumanisation of humanitarian commitments to human-centred development. One of the key recommendations [8, p.30] was that "*an opportunity exists at this early stage to actively engage affected populations in the design, implementation and evaluation of humanitarian predictive analytics ... the contextual knowledge of affected populations and the experience of humanitarian practitioners [can be] combined with the technical expertise of data scientists to improve both the power relationships and predictive efficacy of future innovations in predictive analytics*". Datafication projects that combined the technical knowledge interests of data-science with the emanicipatory knowledge interests of critical social sciences might provide a route to allow affected populations to be active decision-makers in projects designed to affect their lives.

The paper also reviewed datafication of national identification systems, which aim to disintermediate government services and social protection systems. Such programmes can be viewed as driven by the technical knowledge interest to extract data, rationalise decision-making, and enhance control and prediction. Many citizens report valuable gains in convenience and access, and nation states secure gains in efficiencies and governmentality. From the perspective of Habermas' knowledge interests, the technical logics produce knowledge about populations by applying rule-based procedures to empirical data, successfully extending government control over operations and outputs. These disintermediation gains come at the expense of dehumanising relationships between citizens and government. Many of the most marginalised people were entirely excluded by the use of biometric identification. The replacement of human mediated processes of governance with automated algorithmic processes had the unintended consequence of removing rights and entitlements. The black-boxed nature of the AI process and the use of external private corporations and proprietary technologies reduced human mediation and removed accountability and means of redress. These logics are not inevitable, a national identification system could be informed by practical knowledge interests: a public dialogue could run in parallel to the technical build that enables citizens to communicate their concerns and priorities to government in ways that practically inform functionality and system modifications.

Exclusion and extraction were also themes in the third set of digitalisation projects - four digital mapping projects [15]. As in the digital identification examples, data about the most marginalised people was not captured and their realities were not represented in the datafication programmes. Heeks and Shakhar [15] characterised the datafication process as excluding the most deprived individuals and ignoring the most challenging injustices. In both the digital-ID projects and the digital mapping projects, the most marginalised social groups, who are the indented focus of international development, are de-centred and excluded by the digitalisation projects. In the digital mapping example the greatest benefits accrued to external agencies and already relatively advantaged actors, resulting in an overall increase in relative inequalities. These findings resonate with findings from other sectors of digital development [13, 39].

These criticisms of datafication have been accepted by a wide range of actors in digital development and as a result new ethical principles have been produced to reorientate and guide practice. These principles are often explicit in seeking to increase participation and produce a more human-centred AI. Increasing participation holds the potential for disadvantaged people to play decision-making roles at the centre of datafication projects. However, we know from non-digital development that achieving this will not be straightforward [72, 57] if we are to go beyond tokenistic levels of participation. It is in ensuring that excluded voices are heard, understood, and are influential that Habermas' practical and emancipatory knowledge interests have a role to play. Practical knowledge interests constitute social action concerned with understanding and communication. To the extent that datafication projects genuinely incorporate and understand the voices, contextual knowledge, and expressed needs of disadvantaged people, they can be said to reflect practical knowledge interests and communicative social action in the Habermasian sense.

Emancipatory knowledge interests require not only understanding the communicated experience of disadvantaged people, they also requires enabling disadvantaged people themselves to identify the causes of the disadvantage that they experience, as well as their active engagement in social action to remove them. Overcoming injustice and securing freedom from unwarranted domination is the human drive that Habermas argues constitutes emancipatory knowledge interests. This form of social action cannot be characterised by extraction or by exclusion, nor can it be characterised by increased levels of inequality or disadvantage. In such projects participation is not judged by whether more disadvantaged people took part but by whether participants engaged in discussion and reflection about their experience of disadvantage and its causes, and in social action to overcome it.

The various sets of new ethical principles for AI are welcome recognition of some of the negative consequences of datafication. Increasing participation and more human centred AI processes are key to countering the dehumanisation of development but it is easier agree principles that to change practices. There have been claims that the proliferation of principles are in part motivated by corporate ethics washing and a desire to avoid regulation [78, 79]. We will soon be able to assess the extent to which principles translate into participatory practices. Experience from non-digital development suggests participatory practice varies in the degree to which disadvantaged people gain decision-making across the different stages of the development cycle.

6. Conclusion

The paper has argued that datafication can dehumanise development. We have shown the relevance of Habermas' concepts of knowledge interests and participatory development to understanding how datafication can dehumanize development and whether more participatory and human-centred datafication projects are possible. A review of datafication projects in three sectors acknowledged that datafication projects have delivered valuable benefits of efficiency, expanded access, and convenience. The authors have argued that datafication has introduced new actors, technologies and knowledge interests that have resulted in extractive processes, exclusion of the most disadvantaged, and disintermediation of human processes that dehumanise development. In the cases reviewed, digitalisation projects had unintended consequences, including a reduction in the human right to participation and accountability and a relative increase in inequality.

The paper argues that the epistemic underpinnings of data science (technical knowledge interests) conflict with the practical-communicative and critical-emancipatory underpinnings of participatory development, but it does not argue that they cannot be reconciled. The new Ethical AI Principles now being agreed for future digitalisation projects provide a potential route to assess whether a synergy of different approaches to datafication is possible that results in more participatory AI and human-centred datafication. The authors argue that translating principles into practices that avoid tokenstic forms of participation will require the incorporation of practical and emancipatory knowledge interests and the development and use of new planning and evaluation tools to trace the achieved levels of participation of different actors at each stage of the project life cycle. People with a lived experience of poverty and injustice have the right to be included in the design, implementation, and evaluation of any development projects intended to benefit them. Not in tokenistic ways but as authors, architects, and arbiters of their own development.

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