# The Harmful Fetishisation of Reductive Personal Tracking Metrics in Digital Systems

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## ABSTRACT

Personal tracking and the quantified self have grown increasingly popular as technological capabilities for individual insights have grown. Incorporated into many of these systems is the capacity to monitor metrics over time to offer visualisations of attributes such as health, fitness and nutrition. However, many such systems rely on single, simplified measures to represent these complex phenomena, and due to tracking and visualisations, they add value judgements, such as success and failure, to the users' information. This paper, therefore, aims to shed light on the challenges of reductive measures through the case of the BMI (Body Mass Index). The BMI is a clear example of a reductive measure that is used to offer insight into health in both formal and informal healthcare, despite a substantial body of literature that demonstrates other more accurate factors of health that are easily measured. Through a historical consideration of the origin and narratives around the BMI, we demonstrate the fallacy of its use and offer a broader critique of reductive metrics. This understanding of the BMI allows us to highlight the potential harms arising from personalised 'health' tracking technologies and the values encoded into such systems: we use established frameworks of digital harm to demonstrate that using the BMI is harmful for not only well-documented health reasons, but that this harm is exacerbated when it is incorporated into digital technology. Our paper offers a challenge to traditional health thinking and, more broadly, the fetishisation of reductive metrics in data systems.

## CCS CONCEPTS

• **Human-centered computing** → Human computer interaction (HCI); Human computer interaction (HCI); HCI theory, concepts and models; • **Social and professional topics** → Computing / technology policy; Medical information policy; Computing / technology policy; Medical information policy; Medical technologies.

## KEYWORDS

Fat Studies, Health Tech, Critical Analysis, Quantified Self, BMI

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## 1 INTRODUCTION

In 2007, The Quantified Self movement was founded by Gary Wolf, a tech journalist and editor, to "enable self-knowledge through numbers" and provide community support and advice [39]. The movement's focus is on the application of digital technologies to personalise health knowledge. Quantified Self advocates draw on Article 27 of the United Nations Declaration of Human Rights - which guarantees the right "to share in scientific advancement and its benefits" - to encourage self-reflection and frame it as a human right to knowledge [86]. The epistemological position behind this movement is a highly individualised perspective on knowledge and action, where participants extend their interpretation of Article 27 to encompass the right to access data about the self. This idea of the self supports a meritocratic framing of life and is based on ideas of individual liberty.

This form of personal knowledge-seeking is aided by the increasing capacity of digital technologies to collect, monitor, track, analyse and depict data. The community created through the Quantified Self movement is a major selling point, as it is both a means of exchanging best practices and for social support in the pursuit of individual knowledge. Individual knowledge is leveraged by many as a means of solving what we term a 'body problem' - anything that an individual deems to be a problem in their own body, including the need to perform better. For example, a body problem could be anything from cellulite, poor sleep or wrinkles to not running a distance fast enough. While some body problems such as poor sleep may be a problem independent of social context, many trackable 'problems' arise from socio-cultural pressure to conform. This dynamic creates a solution-orientated approach which situates any body problem as solvable or able to be alleviated through increased self-knowledge. While the Quantified Self website cautions against generalising findings based on individual tracking, the sharing of knowledge and practices to help other individuals enhance their knowledge and maximise their own body processes leads to the understanding that comparable data can be leveraged in the same way. This ethos of solvability through tracking, therefore, takes precedence over the non-generalisability of self-tracking [55].

Moreover, instilled with meritocratic liberalism, unsolved or unmaximised aspects of the self become an individual failing to collect the right data. As Rose [78] argues, the activation of participation (for example of refugee to asylum seeker, or unemployed to job seeker) creates a meritocratic dynamic which places blame on the marginalised individual for not participating correctly. In the case of 'over' weight, individuals often experience this activation as pressure to lose weight to look after oneself and be healthy as a form of empowerment [8]. The nascent ubiquitous nature of self-tracking practices - for example, the iPhone design to monitor step counts unless told not to [87] - situates individuals who cannot or choose not to collect and monitor their data in an effort to improve themselves as lesser to those who do.

Reductive measures, which we understand as simple metrics which are imbued with social or cultural value beyond their remit as a measure, are crucial to this analysis. Self-tracking, which creates value judgments of individuals, from compliance to acceptability, is largely focused on reductive measures, such as weight, heart rate, or number of steps, as these are easy to monitor and understand without additional equipment or training. Research into risk scores has highlighted the issues around reductive measures, especially concerning the fairness of the measures for decision-making [19, 20]. Yet such measures are popular across individual uses of digital technologies, and often supported by government public health programmes [65].

Some developments in human-computer interaction (HCI) as a field of research can be argued to reproduce the drive for self-tracking and solvability as they have focussed on individualised tracking through digital devices. For example, in 2012, the Quantified Self Institute was founded between Hanze University of Applied Science in the Netherlands and QS Labs LLC in San Francisco [76]. The Quantified Self Institute focuses on personalised health through self-tracking [76]. Built into this individualised tracking with a focus on health behaviours, is the concept of behaviour change [13, 58]. A key aspect of these designs is the focus on metrics which can be tracked over time and visualised to represent the person and the desired change. This body of literature draws on nudge theory [11], including gamification [5], to encourage behaviour change. "Nudge theory", popularised by Thaler and Sunstein [62], draws on behavioural economics, social psychology and decision-making theories to offer ways to shape behaviour by changing the architecture which influences decision-making and influencing those decisions for both individual gain and government policy [36]. Nudge techniques have become popular within HCI research [11] as digital technologies offer a malleable architecture that can be changed to shape actions.

Caraban et al., [11] highlight the 15 cognitive biases that are used to encourage behaviour change in their review of HCI literature. They make the distinction between automatic and reflective decision-making. The dual process model suggests that we make decisions through two paths: reflective is based on thought, reflection and time, while automatic is implicit, unconscious or habitual [88]. Self-tracking and data visualisation for behaviour change fell under reflective decision-making for Caraban et al. [11] and were the dominant type of technology designed for behaviour change they found.

Nudge theory tends to focus on shaping automatic decision-making processes through changing the design of decision-making spaces towards healthy or desired goals and does not require the knowledge or consent of individuals [62]. Caraban et al. [11] demonstrated how the common cognitive biases such as scarcity, where the lack or shortage of an option makes us want something more [14], or herd instinct, where we tend to want to do what other people are doing [25] are used. For example, Kaptein et al. [43] leveraged scarcity by making the option they wanted users to choose appear less available. Findings from Gouveia et al., [35], suggest that social comparison to others through a fitness tracker increased the amount of exercise users did when the amounts were close to each other. For Caraban et al., [11] through their categorisation of digital nudging, there are limited ethical considerations of aiming to change users' behaviour through design. Instead, 'nudging' through the exploitation of cognitive biases through design is positioned as a useful pursuit to improve human behaviour.

However, two key questions are raised when we consider the practice of intentionally changing behaviors through the design of digital space aimed at tracking individual data. Firstly, the potential for malicious or unintentional nudging, whether through reflexive or automatic decision-making, caused by the design of digital space, and secondly, the question of 'good' behaviour: what constitutes good, and who gets to decide this? In the study by Gouveia et al. mentioned above, [35] they found that herd instinct only supported increased exercise through comparative tracking when a user was within close range of others; when users were further away from the average, the perception of distance decreased the amount of exercise they undertook. Gouveia et al. [35] argue that the unintentional consequences of nudge design on behaviour are largely unstudied.

Moreover, scholars such as Lupton [55] have highlighted the need to understand the specific values embedded within technologies to understand the power embedded within them. Lupton's [55] work emerged in response to the wider trend of the promotion of quantification and self-tracking in health and public policy circles. Lupton [55] argues that the active participation of individuals in tracking aspects of their lives creates a focus on goal orientation, whether intentional or not. In other words, the mechanism of tracking itself embeds goals into our lives and thus shapes behaviour.

Additionally, Lupton [55] highlights the lack of oversight on the data gathered, as the controllers of the data are not generally the user of a digital technology, and the power imbalance this creates is ultimately coercive. This is especially poignant when the focus is personal health data and users who are unable to decide which metric they are maximising instead defer to the technology itself to nominate the aspects of life that should be tracked and changed.

The intentional practice of nudging illuminates the potential for misdirection, control or erroneous assumptions being built into technologies, whether intentional or not. At both the automatic and reflective decision-making stages, users can be affected by the digital environments they inhabit. In line with Lupton [52–55] we argue that there needs to be a deeper consideration for the harms embedded at the nexus of digital technologies and health due to the increasing popularity of self-tracking healthcare. For this paper, our focus is on self-tracking in the global minority due to the existing research focus in these countries and as a reflection of our lived experience. We would welcome and encourage further research on this topic in the global majority.

A popular and highly influential metric within digital design and societal understanding of health is the Body Mass Index (BMI). The BMI is used within formal healthcare as a proxy for health status and diagnostic tool [45], in addition to being a popular metric embedded within personal tracking. For the rest of the article, we will focus on unpacking the history and legacy of the BMI as a measure of health to evaluate the impact of the BMI formula within digital technologies. By focusing on the BMI, we present a deeper challenge to the conception of self-tracking and the reactionary design that underpins it based on the fetishisation of reductive metrics. We argue that the BMI as a metric upholds the meritocratic framing of the self (discussed above) and is a perpetrator of harm through the choice architecture in digital systems which as a default track BMI for health.

As such, the rest of the paper is structured as follows: the next section will give an overview of the trend towards data personalisation and a focus on metrics to outline the broader issue of reductive measures that this paper seeks to question; the case of the BMI is then outlined, from the problematic history to the equation for weight and health that it supports. Next, we situate the BMI as an algorithm, and we apply Mehrabi et als. [60] framework for algorithmic bias to the use of the BMI in digital systems; we then discuss this analysis and highlight the extent of the harm enacted by this one reductive measure. Finally, we conclude by questioning the wider implications of reductive measures in digital systems writ large. As a paper which interrogates the concept of the BMI in digital systems through the lens of algorithmic bias as set out by Mehrabi et al. [60], our paper contributes to the critical interrogation of foundational aspects of existing and emerging data practices and their connection to harms and risks.

Our novel contribution is the explicit linking of established digital harms literature to the evidence of the use of the BMI to anti-fatness in society, building on forthcoming work [81] which establishes that HCI as a field relies on the BMI as a health metric and expanding the fat-liberation perspective in HCI. In this paper, we choose to focus on fatness, reflecting our lived expertise and the asymmetric harm that the BMI causes for people who fall into the high end of the spectrum. We would welcome research which focuses on the lived experience of exclusion due to lower weights, which would complement our work. By showing the extent of the digital harms of the BMI from a fat liberation perspective, this paper offers a unique insight for health tech designers, which we do not believe exists already.

Additionally, we want to note here that this paper includes a discussion of the BMI, calorie tracking and specific weight-related terms, such as 'obese,' which may be sensitive content for readers who have, or have had, an eating disorder. We note this as conservative[1] estimates of the prevalence of eating disorders suggest that around 1 in 10 people [30] will have an eating disorder in their lifetime, and we do not wish to cause those affected further harm.

## 2 PERSONALISATION AND METRICS

Personalised medicine promises healthcare tailored to our own individual genetic makeup [57]: similarly, the rise of the 'quantified self' and the use of health and fitness tracking apps described above promises personalised health and wellbeing guidance. The goal, in both cases, is to, as Kaplan [42] describes, "use data, including real-world evidence, for informing care tailored to each individual" (p.537).

In the context of self-tracking, numerical data - in particular - is seen as 'neutral' and scientific [53], removed from the messiness of bodies and their associated emotions [54]. But this idea of data as objective and neutral has been heavily challenged even as quantified self-practices have risen in popularity: Kitchin and Lauriault, for example, point out that data collection and storage frameworks - such as the monitoring and input functions on wearables and health apps - shape what analysis can be done on the data and the questions that can be asked of it [47].

As a result, as Huijer and Detweiler [40] point out, the options to personalise health apps only go so far: "the overall approach is the same for all users: be active and eat and sleep well to meet goals" (p.232). Apps normalise the idea, for example, that sleeping a certain number of hours is a 'healthy' behaviour: while a user may be able to change the target number, they cannot change the fact that a target – a form of goal orientation, as described by Lupton [55] and discussed above - is seen as 'healthy.' Quantifiable metrics are seen as the goal and the target against which users should be measured. As Zwart argues, the data collected (whether it is detected by a wearable or input into an app interface) must be compared to an external standard chosen by the design team: an optimum which the user should aim for [95]. The harms of these design choices have been highlighted by scholars such as Eikey [21] and Gorsuch [34], who evidence the impact of fitness and calorie tracking on people with eating disorders.

Zwart further argues that self-tracking and personalisation require the user to disclose *everything*: to input more and more data, on the assumption that it is all relevant to the individual's health and wellbeing [95]. Zwart and others (see, for example, Lupton [54], Purpura et al. [75]) have pointed out the surveillance dimensions of this constant data collection, which also plays into the fetishisation of 'big data' as the solution to all human problems (see, for example, Catherine D'Ignazio and Lauren Klein [18] p.151). However, it is also useful to point out that, as with all kinds of data collection, collecting *more* data doesn't mean collecting *more useful* data. As we shall see in our discussion of the BMI below, it is worth examining whether the data and metrics in use in health and fitness apps and wearables are useful at all.

## 3 THE PROBLEM OF THE BMI

The BMI is a widely used measure which is used to signal the relative health of individuals based on a single number – calculated from weight and height – and its comparison to the aggregated average [44].[2] The BMI was adopted by the World Health Organisation [WHO] in 1995 as an appropriate international measure for adults and children [48] and as a diagnostic healthcare tool [45]. Consequently, at the individual level, personal BMI is routinely framed as something to be controlled through diet and exercise. Following the adoption of the BMI by the WHO, it is now commonly used in healthcare practice around the world and tracked globally across all 195 countries as a measure of interest [26]. The increasing global average BMI has been framed as an area of concern, as higher BMIs have been linked to economic expense [64], chronic health conditions [92] and early mortality [2, 23].

[1] We use the word conservative to highlight the lack of reporting and treatment-seeking in many patients [51] and anti-fat bias in the medical profession, which means patients with higher weights will not be diagnosed with eating disorders [67]. Both of which reduce the number of recorded cases of EDs and reduce the estimated number of the prevalence of EDs.

[2] The BMI for an individual is calculated by dividing that individual's weight in kilograms by the square of their height in metres.

However, since the popularisation of the BMI measure, scholars and activists have worked to disentangle these claims from the stigmatisation of fat people. As early as the 1980s, the link between higher BMIs and mortality has been questioned [27], as many of the factors which cause death at higher BMIs can be explained through the focus on weight by healthcare practitioners instead of treating the symptoms. Flegal et al. [27] found that higher BMIs were not causal for morbidity. Moreover, as we increase our understanding of chronic health conditions, the links between such conditions and BMI become more nuanced. For example, researchers into diabetes have suggested that the relationship between weight, insulin resistance and type two diabetes is more complicated than higher weights causing insulin resistance and then diabetes, but instead, an interrelated mechanism of insulin resistance leading to weight gain and type two diabetes [17]. Moreover, the American Medical Association (AMA), has recently acknowledged the limitations of the BMI as a metric for individual health [3, 71].

Yet, despite contradictory or inconclusive evidence of the effectiveness of the BMI as a proxy measure for health, and medical practitioners moving away from the BMI as a useful metric, public policy foregrounds the individual and collective control of weights, implementing calorie and food labelling in restaurants and supermarkets [67]. Healthcare focuses on weight loss and BMI reduction, which, in many cases, is a prerequisite for other treatments, including gender-affirming care and many reproductive services[3] [4, 56, 89]. So, why, then, is the BMI still a popular measure of health? The next section considers the evolution of the metric to give an overview of how it has become central to healthcare practice.

## 3.1 Historical and Racialised Origins of the BMI

Originally called the Quetelet Index in 1832 [22], the BMI began as a population measure of "social physics". This measure plotted the normally distributed curve of weights based on the available data, including Belgian official statistics [70] and, most famously, measurements of the chest sizes of 5,738 Scottish soldiers [70]. Quetelet, a statistician, astronomer, and polymath, defined categories of the curve based on percentiles of the data [48]. The 'normal' weight band fell at the top of the normally distributed curve of weights, and for Quetelet, this 'average man' formed the ideal man [22]. However, Quetelet's categories (under, normal, and overweight) were subject to change as the distribution of weights in the population-level sample changed. Karasu [44] argues that the labelling of the categories as over and underweight instead of over and under the average weight makes the normative ideal a standard to achieve instead of a statistical category. Quetelet's fetishisation of the average man - despite his own belief that his index represented the population and should not be individualized - was then framed as an individual measure of success and popularised by Galton to support social Darwinism and scientific racism, and ultimately justify eugenics projects [77].

By moving from a population-level measure to one of individual success, the BMI offers a clear example of a "fetishised metric". As Galton's work showed, the BMI was easy to use and operationalise at the individual level [6]. The metric of the BMI is considered important, to an unreasonable degree compared to its applicability and relevance, as shown by recent work in the medical community [3, 71] and is, thus, fetishised. While the scientific racism, which underpinned the BMI, has been disproven [77], the focus on individual BMI by medical professionals has remained. The ease of using the BMI was further popularised by health insurance companies in the US to increase insurance premiums for sections of the population [32]. Until the 1970s, there was no standardisation of the levels of 'unhealthy' weight, as they were set at the discretion of the various insurance companies [61]. However, as increased revenue was available from the weight loss and management industries and the rise of big pharma, industry-wide standardisation has lowered the cut-off points for weights classed as unhealthy [33, 65].

For example, in 1995, the WHO lowered the cut-offs for categories (overweight, normal and so on) and classified more people as unhealthy - against the panel of expert advice [65]. This decision has since been shown to have involvement from the pharmaceutical companies Abbot and Roche, who were consequently able to bring weight loss drugs to a larger market following the change of the categories [61]. The global weight loss market is expected to surpass USD 405bn by 2023 [49]. Cairns and Johnston [8] highlight the embodied neoliberalism that encourages women, specifically, they argue, to engage in dieting behaviours. Thus, the combination of financial incentives, ease of use and hierarchical domination created by the BMI leads authors in Fat Studies to conclude that this measure is not only harmful but upholds intersectional oppression [16, 32, 33, 37, 65, 79], which benefits a select few. Despite increasingly wide recognition that the BMI is a flawed measure because of its limitations and its history of harm (see for example [3, 41, 71]), it remains a popular metric in health worldwide.

## 3.2 BMI as an axis of oppression

Fat Studies [24, 79] highlights the way fat[4] bodies, those identified by the BMI as overweight, obese, morbidly obese and so on, are oppressed not only by real-world treatment but also by the assumptions embedded within the categories. Assumptions about fatness contribute to stereotypes of laziness, poor willpower, ill health, and gluttony [28]. Gordon [33] argues that the racially motivated dislike of fatness came first, and medical compliance, incorporation of the BMI into standard practice and research aiming to justify the harms of weight followed. The proliferation and real-world impact of the assumptions is shown by findings from the Harvard implicit bias test, which found that 80% of people held implicit anti-fat bias, the only kind of implicit bias that has not diminished over the 2000s [83]. The consequences of this bias have been evidenced in healthcare outcomes [10, 69, 90], the legal system [93], reduced pay [50], employment [31], and wellbeing [91][5].

[3]Sources cited for this claim are focused on the global minority and refer to westernised healthcare settings. Specifically the US [4], Canada [56], and New Zealand [89]. As such, we would like to highlight the range of privatised and nationalised health services that rely on the BMI as a barrier to care.

[4]Fat, in this context, is used as a neutral descriptor following the work of activists to reclaim fatness from oppression [46]. Anti-Fat bias is used instead of fatphobia as it is a form of oppression thus, "phobia" does not do the dynamic justice [1].

[5]Sources cited for this claim focus on the US (Campos [10], Pearl [66], Anekwe [87], Yamawaki et al., [90], Giel [28]) with one focusing on the Korean context (Lee et al., [47]), and another which was a meta analysis of all available quantitative research on the topic of health outcomes (Wu and Berry [88]).

**Table 1: summary of digital harms from the BMI**

| Location of bias | Form of bias | Digital harms resulting from in the use of the BMI in health tech |
|---|---|---|
| Data to algorithm | Aggregation | Conclusions drawn about individuals from a population |
| | Representation | BMI developed using data from Belgium and Scotland, but applied worldwide |
| | Measurement | Prioritisation of an easily-calculable measure over other measures of health |
| | Omitted variable | Omission of other metrics outside of height and weight |
| | Longitudinal data fallacy | Drawing conclusions about the impact of BMI change, from data about cohorts with different BMIs |
| Algorithm to user | Algorithmic | BMI categories used to distinguish between 'acceptable' and 'requiring intervention,' independent of health research |
| | Evaluation | BMI problematic metric for health |
| User to data | Historical | Use of an established but problematic metric in new technology |

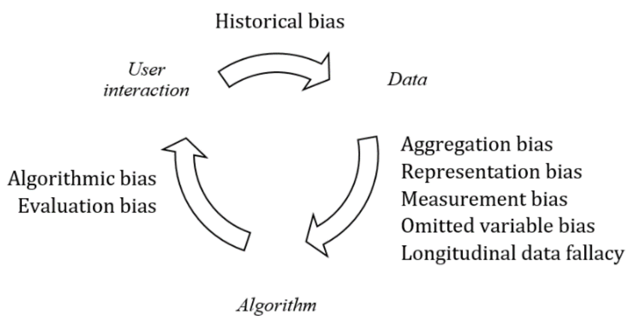


**Figure 1: digital harms from the BMI, represented using Mehrabi et al.'s cycle diagram**

The use of the BMI as a tracking metric situates fatness as a choice, a symptom of ill health, and as controllable [33]. The framing of fatness as an obesity epidemic, with some more recent suggestions of a syndemic or synergistic epidemic of "obesity, undernutrition and climate change" [84] , has been argued to be incredibly harmful [59, 65]. Based on these grounds, the mistreatment of fat people is rationalised and reproduced across society [37, 65]. Fat Studies suggests that by unpicking the power politics that support anti-fatness, from the colonial origins [82] and normative body standards [89] to the economic motivations [49] and the use of the BMI to create an obesity epidemic [65], the potential to reframe discussions around fatness and challenge harmful practices. By helping to uphold framings of fatness as a body problem to be solved, the BMI supports intersectional oppression across gender expression, class, ability, and racialised expectations of the body [37, 79]. Thus, the BMI as a metric holds an important role in systematic power and is an important focus of study.

## 3.3 Digital harms of the BMI

In addition to the well-established harms of the BMI described above, the use of BMI within health and fitness wearables and apps adds an extra dimension: the digital harms of the BMI which have previously been overlooked by designers of health related apps [66]. In this section, we use the framework developed by Mehrabi et al. [60] to illustrate how bias - one sform of harm - can enter and be amplified into a feedback loop from data to algorithm (in this case, the model of the BMI), from algorithm to user interaction, and from user interaction into data.

In this section, we are using the BMI as a mathematical model: a deterministic algorithm which produces outputs from inputs. For each individual, the input is two variables: height (in metres) and weight (in kilograms); the output is produced in two forms: a number (calculated as the weight divided by the square of the height), and a qualitative output. For example, according to the NHS website in the UK, for white people (different outputs are used for different ethnicities), a BMI below 18.5 is **underweight**, between 18.5 and 24.9 is **healthy,** between 25 and 29.9 is **overweight**, and of 30 or over is **obese** (emphasis added) [9]. We present a summary of the harms we have identified from the use of the BMI in table 1 below.

## 3.4 Data to algorithm

The unquestioning use of the BMI - a model calculated from the underlying measurements of weight and height - allows for bias to enter into models and recommendations produced by health technologies. The problems with the BMI described above are themselves a form of **aggregation bias** (also termed ecological fallacy), where conclusions are drawn about individuals from observing the entire population. The origins of the BMI is itself a form of **representation bias**: as discussed above, the BMI draws on the work of Adolphe Quetelet, using data from Belgian and Scottish white males. These datasets, while they may have been the best available to one of the earliest statisticians, cannot be said to generalise to the rest of the world.

The choice of BMI as a proxy measurement for health is a form of **measurement bias** - the choice of an easily available and calculable figure over other quantitative and qualitative measurements of health such as blood pressure or quality of life assessments. The focus on BMI - calculated from just two variables - also allows for **omitted variable bias**, defined by Mehrabi et al. as leaving one or more important variables out of a model. The BMI is an extreme example of this, omitting almost every variable that has been shown to be relevant to health: for example, cardiovascular fitness, which has been shown to account for excess mortality amongst obese men [10].

More insidiously, the use of BMI for individualised, 'personalised' models and recommendations can be seen as a form of **longitudinal data fallacy:** where different cohorts at one time are used to model a single cohort over time. [60]. In this case, the different cohorts are people with different BMI statistics, rather than the same people with changing BMIs observed over time. However, even when there is evidence that people in certain BMI ranges have a higher risk of excess mortality (for example, for men in 'moderately low' and 'extremely overweight' categories in Troiano et al. [85]), this is not necessarily evidence that an individual changing their weight, and thus their BMI, changes *their own risk* of mortality. The longitudinal data fallacy rationalizes the idea that changing a person's BMI will change their health outcomes and justifies the use of the BMI as a health metric, which, as discussed above, situates fatness as a choice and something that is controllable.

### 3.5 Algorithm to user

This section examines the ways in which the BMI model introduces biases into the feedback loop through the ways in which the algorithm - in this case, the BMI model - is shown to users. The fact (described above) that studies show that people with an 'overweight' BMI do not have an increased mortality rate compared with people with a 'normal' BMI [27] can be seen as a form of **algorithmic bias**: while the actual risks are the same, the use of BMI and its qualitative, value-judgement categories in health and fitness apps makes a distinction between the two categories: labelling one as acceptable and the other as requiring intervention.

The use of the BMI also represents **evaluation bias**: the choice of a metric that is inappropriate for the setting. As described above, BMI is a problematic metric for health in a range of ways: most importantly, for the use in health and fitness apps and the recommendations they make to users, there is no evidence that for an individual, changing their BMI (which in practice means changing their weight, as height is static for most adults) changes their health [10].

### 3.6 User to data

The BMI - unlike many other algorithmic systems in use - is not constantly being changed with the input of more data. However, it is worth noting that it is not an entirely static model. The underlying formula - the calculation of weight over height squared - has not changed, but the categories to which the resulting numbers are assigned have (including by the WHO, as discussed above [61]). The changes have not, to our knowledge, been prompted by the rise in the use of health and fitness technologies; however, it is worth noting that the fact that the BMI remains an important component of health and fitness apps represents a form of **historical bias** - the seeping in of existing socio-technical issues into the creation of new technologies. Despite the demonstration of its flaws described above, the BMI remains an important model, even in papers critical of the datafication of health, for example Purpura et al [75].

In this section, we have used the framework of bias as a form of digital harm to explain the ways in which the BMI - for decades taken for granted as a proxy for health - can cause harm when unquestionably incorporated into health and wellness technologies such as wearables and apps. Even just considering bias - one component of the potential harms that can be done by digital technologies - shows a significant array of harms.

## 4 DISCUSSION

The case described above has shown how the BMI as a reductive measure can ingrain harm into algorithmic processing. More broadly, we argue it illuminates two things: firstly, due to the popularity of the BMI as a metric in digital decision-making, the potential for systemic algorithmic harm, specifically in relation to weight and anti-fat bias, to be propagated through the fetishisation of this reductive measure. This digital environment and architecture, suggests that the BMI – and weight as the only "controllable" element of the measure – is a problem to be solved and ingrains being 'over' weight as a body problem. Secondly, the case of the BMI highlights how easily a simple measure used as a proxy can infiltrate and permeate our social world to cause harm: we have termed this fetishisation. Thus, beyond the BMI, this paper contributes to the critique of the notion of self-tracking, goal orientation and single reductive measures in digital design.

This article and the focus on the BMI have shown the possible harm that reductive measures such as this can have when embedded into personalised health tracking. As discussed earlier in the paper, previous critiques of personal tracking, such as Lupton [52, 53, 55] and Sikka [80], have highlighted the exploitative financial interests that alter the landscape of digital tracking. We develop their arguments by offering a consideration of the embedded bias in digital tracking through the microcosm of the BMI as an algorithm. Lupton [55] frames the issues of personal tracking technologies as a blurring of the boundary between personal data practices and big data practices used as a managerial technique to question the control and power embedded in the big data practices of self-tracking technologies. By situating the BMI as an algorithm, we can see the way that this measure at the algorithm-to-user stage, creates a body politic at the population level which ascribes different values to arbitrary categories as a management technique. Moreover, at the user-to-data stage this management technique is made clearer as the historical bias which has set the (changing) boundaries of the categories shows the social-political framing of the BMI algorithm.

Recently, the financial interests of Abbot and Roche [61] associated with reducing the weights at which categories of the BMI start – creating millions more "over" weight or "obese" people overnight – have been revealed[6]. This change in boundaries increased the number of patients considered to have a body problem by insurers, and altered the user-to-data stage of the algorithm supporting Sikka's [80] argument for the dietary-genomic-functional food industrial complex. Sikka [80] develops an understanding of the power within the new data practices of health and wellness technologies (as we have discussed, popular sites of BMI tracking) by considering the

[6]The changing boundary on the BMI categories described here, could be considered social bias (as defined by Mehrabi et. al within their 'user-to-data' category), as it is a change in the algorithm as a result of human judgement. The lowered cut-offs become a form of social and medical pressure, which was later exacerbated by the prolific existence of the BMI in digital technologies. However, we have not included this explicitly in our analysis, as the change arose from the financial interest of companies instead of from user-to-data influence.

intersection of race, gender and class to highlight the manifestation of injustices. In addition to the historically racist development of the BMI, which highlights Sikka's argument at the user-to-data stage, the data-to-algorithm stage shows the multilayered biases based on discriminatory assumptions that are incorporated into the BMI as an algorithm.

Considering the BMI as an algorithm offers the ability to unpack the specific digital harms being embedded into virtual health environments using the BMI. Designing technologies to specifically exploit users' cognitive biases to promote certain behaviours and reduce others obfuscates the process from users and foregrounds one, exclusionary, understanding of health. This form of design is focused on individualising solutions to problems, further isolating those who do not, or cannot, meet the prescribed standards. These conditions imposed upon digital space are insidious, they are hard to see and they are hard to challenge due to the complex financial interests they contain. We see the embedding of the BMI through such technologies as not only discriminatory, but dangerous.

There are of course limitations to our analysis here. Principally, addressing the digital harms caused by the BMI will not address the spectrum of injustices which currently exist in the medical systems of countries around the world. The right of everyone to the enjoyment of the highest attainable standard of physical and mental health, guaranteed in Article 12 of the International Covenant on Economic, Social and Cultural Rights, will require addressing not only the harms caused by the BMI and problems arising from the use of health tech, but also broader injustices which affect access to healthcare worldwide.

Moreover, as we noted earlier, the literature we cite in this paper is primarily focused on global-minority settings in the west, as this is where the majority of research has been undertaken. We have evidenced the prevalence of the BMI as a health metric and barrier to care in higher-income settings [4, 56, 89]; with the global financial pressures on providing healthcare, reductive metrics offer an appealing, low-cost option for lower-income settings. We are concerned, therefore, that the prevalence of the BMI and other reductive measures in global-minority-developed technologies may be exported to the global majority, together with discriminatory practices, body size prejudice and the associated digital harms.

Consequently, future work on the global impact of the BMI is a top priority. In addition, we suggest an analysis of the physical harms associated with the digital foregrounding of the BMI, and the impact of this digital environment on those who could face stigma for being categorised as 'underweight' by the BMI metric, as this was out of the scope of this paper. While much work has considered online spaces and eating disorders [12, 29, 34], an approach to such from a fat liberation perspective could be fruitful to shed further light on the intersectionality of the harms of the BMI as a measure. We would also prioritise empirical work focused on the specific experiences of fat people using health technologies, as this group has been vastly underrepresented in research, and point to Payne et al. [68], for discussion on how to ethically engage fat people in HCI research and Fletcher [28] as an example of autoethnography in this area.

More broadly, by highlighting these biases in the BMI, we argue that the popularity of personal tracking can be understood as an irrational or excessive devotion to reductive measures and is, therefore, a harmful fetishisation of such measures. This understanding of embedded bias challenges the acceptance of goal-orientated tracking and allows users and designers to consider how their use of popular features could be re-creating harm. Moreover, the microcosm of the BMI has allowed the nuance and mechanisms of bias in measures to be foregrounded.

The BMI and its use in healthcare specifically have been shown to cause harm as doctors' weight bias [72–74] reduces the quality of care patients receive and creates strained relationships between patients and medical professionals. Moreover, the focus on the metric of the BMI and success through this measure means that people with larger bodies are less likely to be identified as having eating disorders and instead will be praised for weight loss: in other cases, weight loss is celebrated and not questioned resulting in serious illnesses such as cancer go undiagnosed [90]. As we move toward digitised services, healthcare and reporting, the ability to question or opt out of practices is being curtailed, and the digital harms of metrics such as the BMI are becoming unavoidable and obfuscated by the digital technologies they are built into. Yet, 15 minutes of anti-fat bias training for healthcare professionals can seriously improve fat patient outcomes [63]. This finding suggests the focus on the BMI as a central metric can be alleviated, and it offers space in digital design to challenge and counter harmful reductive measures [19, 20].

The BMI as a case is unique in so far as the algorithm described is widely understood and openly used. When we apply our argument more broadly to complex digital tracking systems which aim to change behaviour and nudge people towards a goal, questions of cognitive bias and black-box algorithmic decision-making are raised. If, as Lupton [55] argues, tracking creates a goal orientation, when designing digital tracking technologies, who decides what to track and which goals are, therefore, validated? Another area of investigation into reductive measures in health tracking could be the visualisation of blood sugar through increasingly available wearable blood glucose monitoring sensors [38, 94]. The colours picked to represent blood sugar are coded red-green in the monitoring app from Freestyle-Abbott, and thus could imply a judgement of the glucose level. This formation has varying implications for people who are curious about their personal breakdown of food compared to those with diabetes and who manage this chronic health condition. The reduction of success to one number or colour when diabetes, type 1 or 2, is a complex condition with a multitude of variables has potential implications for the experience of the app users.

As such, we ask what this tracking means for users: how does the decision to track certain aspects of life (from the period tracking in fem-tech, to measures used to signify health such as number of steps, sleep tracking, or calories eaten) exclude and marginalise those whose bodies, capabilities or choices deviate from the desired state? Consequently, we ask if it is even possible to design in a goal-oriented way that isn't reductive or inappropriate for some users? These questions arise from this paper as a means of thinking about the way we design beyond reductive metrics and towards an inclusive and complex set of futures.

To encourage developers and designers of health tech to think beyond the BMI in their work, we offer the following reflection questions. We have developed these drawing on the Design Justice

Principles outlined by Costanza-Chock [15]: and informed by the body size and fat liberation movement:

- Are you considering the needs and wants of fat people in your design, and are you assessing the impact of your design on fat people?
- If you are using health metrics in your work, what definition of 'health' is promoted through the metrics you're using? How does this definition of health impact the communities you are designing for?
- How are you supporting the user of your tech product to understand change in the metrics you are using as part of an ongoing process, rather than as a goal to be attained?
- How is your technology facilitating users to learn and explore data related to their own health without encoding value judgements into the process?

# 5 CONCLUSION

In this paper, we discuss the rise in the use of self-tracking, personalised health apps and wearables, many of which use the Body Mass Index as a metric. We have shown that the BMI is a simplistic metric which has little connection to health but which is strongly linked to the stigmatisation of fat people. Nonetheless, this fetishised metric remains in use in health sectors worldwide and has been adopted by the developers of health-tech as a metric for monitoring users' health.

We build on this understanding of the BMI to document the additional harms arising from the adoption of this metric in digital technologies, using the digital harms framework developed by Mehrabi et al [60]. We show that - considering the BMI as an algorithmic model in this framework - harms enter into the system at all stages (from data to algorithm, from algorithm to user, and from user to data) but that they are particularly concentrated in the 'data to algorithm' stage.

In particular, the use of the BMI in health-tech demonstrates aggregation and representation bias, as a metric developed from a small group of people in 18th century Europe; and it also demonstrates measurement and omitted variable bias, as it ignores useful - but harder to measure - health metrics in favour of a model based on weight and height (which are easy to measure). More insidiously, the use of BMI as a target for users to meet can be seen as a form of longitudinal data fallacy: there is little evidence that changes in an individual's BMI correlate with changes in health, but the assumption that this is possible contribute to ongoing stigma and harm to fat people. Fundamentally, we call for designers of health technologies to question and rethink using the BMI as a valid measure of anything beyond a measure of density[7], to support a justice-oriented framing of digital health.

Beyond the BMI, we offered a consideration for the use of other reductive and goal-orientated technologies. Who gets to pick what goals we are expected to reach, and by what measures success is granted? The adoption of data visualisation and tracking across ubiquitous computing has been critiqued by many scholars, but the example of the BMI shows how these concerns are forcibly embodied by those living in deviant bodies. Our paper challenges traditional health thinking and, more broadly, the fetishisation of reductive metrics in data systems. We encourage designers of health-tech systems to look beyond simplistic measures like the BMI and to consider health in a holistic, non-stigmatizing way.

[7]The units are usually omitted in discussions of the BMI, but if it is to be considered as a scientific quantity, it is a measure of area density and should be expressed in $kg/m^2$.

## 5.1 Ethical concerns

We include in this paper a content warning for discussion of the BMI, calorie tracking, and specific weight-related terms such as 'obese': this is to enable people who have or had have eating disorders (conservative[8] estimates of the lifetime prevalence of eating disorders put this at around 1 in 10 people) to make an informed decision about whether to, or when to, engage with this paper.

This paper, as a critical engagement with the use of the BMI, did not include any research on or with individuals. We encourage research into the use of healthtech and wearables to problematise any use of the BMI or other reductive measures as part of their ethical considerations.

## 5.2 Perspective statement

The authors write from the standpoint of fat people who want to live, as Butler [7] describes, livable lives. Personal experiences with healthcare and the BMI have adversely affected both authors, primarily within NHS services in England.

## 5.3 Adverse Impact

We cite in this paper a number of works which rationalise and justify the use of the BMI in health measurements. We would like to emphasise that we cite these to illustrate the widespread use, and not in support of this.

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