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Exposing Civic Normativity: Applying the Persona-Based Walkthrough Method to the Dutch Happiness Meter

Abstract: This study analyzes the Dutch Happiness Meter (HM) – a digital tool employed by the government to quantify citizens' happiness – through the lens of critical data studies. We introduce the "persona-based walkthrough method" to explore the HM's algorithmic underpinnings and its socio-technical construction of happiness. By navigating diverse personas through the HM's interface, we answer the following questions: RQ1: How does the Dutch Happiness Meter (HM) embed socio-cultural norms and biases within its algorithmic design, and how do these translate to the quantification and representation of citizen happiness across diverse demographic groups? RQ2: How does the persona-based walkthrough method reveal the limitations and exclusions of black-boxed e-government applications such as the Happiness Meter, and how can this method contribute to algorithmic accountability and transparency in digital governance? and RQ3: What are the implications of datafying subjective well-being through tools like the Happiness Meter on public perceptions of happiness, and how does algorithmic governance influence the epistemologies of well-being in the context of policy-making and societal inclusion? The analysis untangles cultural and computational synergies, examining their influence on civic normativity and quantified well-being. Our contribution shows how such data-driven systems construct a normative understanding of happiness which impacts governmental strategies and public accountability. The findings reveal critical insights into the underlying assumptions and biases in the HM, particularly how socio-technical systems shape user experience and influence perceptions of well-being. By employing personas, especially "anti-personas", the study exposes civic normativity as mechanisms of exclusions and inequality. This study aims to contribute to discussions on digital governance's role in shaping societal perceptions of well-being, highlighting the need for algorithmic accountability, transparency and inclusivity in algorithmic e-governmental infrastructures.

Keywords: digital government; measuring happiness; walkthrough method; datafication; algorithmic governance; persona's; virtual ethnography

Introduction

As the datafication of society progresses, the role that algorithms play in decision making processes increases with it.[1] This growing reliance and pervasiveness has major consequences for our everyday lives (Kitchin, 2014). Algorithms generally are black-boxed systems (Pasquale, 2015), perceived as complex objective mathematical entities (Seaver, 2017), whose workings are impenetrable. The scores they produce are often depicted as a representation of "objective" statistical data, and therefore interpreted as factual (Gillespie, 2014). Contrary, perceiving algorithmic systems as non-neutral implies that algorithms are shaped by all kinds of decisions based on politics, ideology and culture. Thus, algorithms are embedded in the politics, ethics and aesthetics of their birthplace, and are both limited and conceived through a material and immaterial infrastructure.

A non-neutral perception of algorithms becomes even more important when governing institutions use them for their decision making processes. The digitalization and datafication initiatives of governments are integral to their algorithmic governance strategies and their pursuit of sustainable development goals, often incorporating the measurement of civic happiness. Measuring of citizens' well-being fits a global trend, and has been pushed by the Sustainable Development Solutions Network (2018) of the United Nations. E-governmental infrastructures that collect, evaluate, or depict citizens' well-being and happiness often operate under the pretense of neutrality and objectivity, overlooking the socio-technical dynamics inherent to these systems. Against the backdrop of an expanding governmental emphasis on quantifying citizens' well-being and happiness, alongside demands for open government approaches, sustainable development, and enhanced public accountability, this paper examines the *Geluksmeter* (translated as "Happiness Meter", abbreviated as HM). It aims to dissect

[1] When discussing "algorithms" we believe it is productive to move beyond a mere technical appreciation thereof as "instructions fed to a computer". Instead, we take them to be heterogeneous socio-technical systems following Seaver (2017). Such socio-technical systems are "technical constructs that are simultaneously deeply social and cultural" (Seaver, 2017, in Wieringa, 2020). Algorithmic systems can be massively complex, such as Neural Networks, or be very simple, as in the case of decision trees, or somewhere in between (e.g. regression analysis).

the socio-technical interpretation, quantification, and integration of happiness and well-being within the framework of algorithmic governance. Ascertaining that the HM is a non-neutral (semi-)governmental system, and therefore needs scrutiny and examination of its epistemological underpinnings, we combine a critical data studies perspective rooted in media studies and science and technology studies, in pursuit of the following questions; RQ1: How does the Dutch Happiness Meter (HM) embed socio-cultural norms and biases within its algorithmic design, and how do these translate to the quantification and representation of citizen happiness across diverse demographic groups? RQ2: How does the persona-based walkthrough method reveal the limitations and exclusions of black-boxed e-government applications such as the Happiness Meter, and how can this method contribute to algorithmic accountability and transparency in digital governance? and RQ3: What are the implications of datafying subjective well-being through tools like the Happiness Meter on public perceptions of happiness, and how does algorithmic governance influence the epistemologies of well-being in the context of policy-making and societal inclusion?

This study presents a virtual ethnography for analyzing black-boxed algorithmic systems like the HM. Coined as "the persona-based walkthrough method" – consisting of the "walkthrough method" (Light et al., 2016) augmented with a persona-based engagement with an interface – our method explores e-governmental systems by "walking" a plethora of diversely constructed personas through the black-box, and analyzing the disparate differences in output and visualization. These constructed personas allow the black-boxed algorithm to be understood by its "disparate impact" differences, which have the potential to influence legally protected classes of people or invoke regulatory response (Seaver, 2017). This enhances the conventional walkthrough technique, aligning with the theoretical and methodological underpinnings of critical data studies (Duguay & Gold-Apel, 2023), and reveals the mechanisms of data infrastructures within digital governance, enabling a thorough inspection and facilitating accountability of such systems. Drawing from this reasoning, we argue that the HM advances a narrowly conceived but powerful realist epistemology – society perceived through data as factual, objective and neutral – that is reshaping how people come to know happiness.

An analysis of such a case is valuable for three reasons; 1) the quantification of eudaimonia and similar elusive lived experiences should be assessed carefully and critically, 2) data/algorithmic systems informs policy,[2] and 3) as will become apparent in the analysis, the data-assemblage which drives the present case, excludes particular groups. The system constructs a normative framework through the graphic presentation of selective choices in gender, ethnicity, age groups and more, in which

[2] In this case this takes the form of a report that functions as an instrument to present a happiness score constructed upon socio-economic data provided by the CBS (2016).

socio-cultural norms are produced and/or performed. This results in a partial perspective, which favors the demographic norm, and facilitates social inequality.

The Happiness Meter: Measuring happiness or performing normativity?

In 2016, the Dutch quasi-autonomous non-government organization (QUANGO) Statistics Netherlands (*Centraal Bureau voor de Statistiek*, CBS), developed and launched “the Happiness Meter”. The Happiness Meter (HM) calculates a personalized score relating to *geluk* (best translated as “well-being” or “happiness”). It draws on an underlying algorithmic system and dataset developed by the CBS, and presents these through its online interface. In the HM, users can calculate a personalized “happiness” score by drawing on an underlying algorithmic system and dataset. In order to calculate this personal happiness score, eight questions have to be answered on a scale from one to ten. After answering these questions, your personal score is visualized within a circular graph and can be compared with average scores relating to a specific demographic group.

The HM was developed based on the report *Welzijn in Nederland* which presents statistical data on the status of well-being, satisfaction and/or happiness of Dutch civilians in 2015 (CBS, 2016).[3] The report functioned as a starting point for the construction of a personal well-being index (PWI). For the calculation of the PWI several surveys are held among the Dutch population to establish average scores within eight dimensions. These dimensions consist of: present financial situation, future financial situation, health, leisure, social life, government, safety, and your living area (CBS, 2016). The PWI is not only used as a tool to represent the status of well-being of various demographic groups within the Netherlands, but also as an instrument to compare the status of well-being in the Netherlands with the overall status of well-being in the European Union (CBS, 2016). Based on the PWI score for specific demographic groups within the Netherlands, policy is developed to increase their well-being, and acquire funding from the European Union (CBS, 2016).

The HM is exemplary of a broad socio-technical trend wherein statistical data is visualized within various interfaces to make the data more accessible, as recently could be seen with election polls, health tests, security tests and other initiatives (Van Dijck et al., 2016). Many countries set up broad projects concerning open data/open “government” (e.g. U.S. General Services Administration, 2018). The phenomenon of measuring the difficult concept of citizens’ well-being fits the global efforts of the Sustainable Development Goals (SDG) of the UN. The UN initiative followed the lead of Bhutan, which was the first country to establish a Gross National Happiness (GNH) as opposed to Gross National Product (GNP)/Gross Domestic Product (GDP) (Burns,

[3] *Well-Being in the Netherlands* – translated by the authors (CBS, 2016).

2011), and even included the strive for happiness in its constitution (Correa, 2017).[4] The Dutch efforts of measuring happiness can thus be placed within this broader context of assessing the well-being of people through quantification and data-sets.

Critiques of happiness measurement and the datafication of emotions like happiness highlight the complexity of capturing affective states (Stewart, 2014), which are tacit, fluid, and influenced by context, sociality, and embodiment (Anderson & Harrison, 2006). Studies reveal the challenges digital platforms face in quantifying such states, as they often overlook the temporal and situational nuances essential to these modes of knowing (Huvila, 2012; Kennedy & Hill, 2016). Moreover, the diverse conceptualizations of happiness and well-being across cultures and time hinder international comparisons. Additionally, data collection on well-being is complicated by self-presentation concerns and cognitive biases among respondents (Oishi et al., 2018).

Accountability in data-assemblages

The legitimacy of a modern Western democracy rests upon the extent of a (semi-) government's accountability (Diakopoulos, 2014, p. 58). Accountability can be understood as the acceptance of responsibility for one's actions, and, by extension, being liable for them (Nissenbaum, 1994). The Dutch require the government – as well as the publicly funded, albeit independent QUANGOs – to account for their actions, as is formulated in the behavioral code Public Government (de Graaf & Huberts, 2011). "Algorithmic accountability"[5] has risen to prominence on the Dutch parliamentary agenda (e.g. Knops, 2018), especially since the widely celebrated General Data Protection Regulation (GDPR) provided something of a supranational legal framework, most notably its "right to explanation"; which is the right of subjects to challenge and obtain insight into algorithmic decision making processes. This right requires that insight – and therefore accountability – *can be obtained* by the institution responsible for the data – or algorithmic fueled technology, and also that such insight is *made intelligible* to the data subject. With this right, a new challenge of accountability dawns for various organizations, including public institutions.[6]

Algorithms – and data systems in general – are often framed as being "objective" and "neutral". Gillespie (2014) questions how people can make claims of "objectivity" when engaging with algorithms, while they mostly depend on highly variable measures and structures of data sets, and the presence of various subjective choices, assumptions and indicators within the algorithm (Uricchio, 2017). This "mantra of

[4] The GNH of Bhutan has been criticized as a way to distract from Bhutan's ethnic cleansing (e.g. Pulla, 2016).

[5] Also called "data-assemblages".

[6] There is also heavy, and justified, critique on the right to explanation (see, e.g. Edwards & Veale, 2017).

objectivity" obscures its roots in human choices and decisions. This is partly due to the characterization of the algorithm as a technical object, instead of a sequence of human based instructions embedded in social practice and culture. As such, we endorse Seaver's (2017) assertion of algorithms *as* culture, where the outcome of actions is considered cultural practice, instead of a specified script in the form of a tradition. Likewise, an algorithm is not one fixed and coherent thing, but an assemblage of interactions, with both social and technical dimensions, and *always in a state of becoming* (Kitchin, 2017, p. 18). Kitchin and Lauriault (2014, p. 2) propose to apply the concept of the "data assemblages" to critically examine and scrutinize these algorithmic data infrastructures. They argue that capturing and storing data within vast repositories and databases cannot be perceived as a neutral means of processing and assembling data (Kitchin & Lauriault, 2014, pp. 3–4). Within this perspective, we are able to describe the socio-technical system that is the HM and analyze the values and norms embedded in it.

The need for accountability comes inherently with the consideration of the subjects on which the algorithmic system has an (potential) influence. We should recognize the soft power of data systems to reproduce (cultural) normativity and the rhetorical power of data, algorithms and visualization, in the process of knowledge production. For that reason, our analyses of the HM prioritize the outcome of human/technology interactions over the materiality of the object, the code of the program, and the problem solving potential of an algorithm. Gillespie (2014) posits that algorithms and software applications are shaped not only by their designers and programmers, but also by the users who engage with them, suggesting a co-creative process in the development of digital culture. While algorithms within systems may remain opaque or "black box" entities, making socio-technical transparency elusive, it is still possible to infer the workings of these algorithms through experimentation with inputs and analysis of outputs. Specifically, by examining the "disparate impact" as defined by Seaver (2017) – the differential outcomes that disproportionately affect certain groups – we can critique and better understand the biases and classifications embedded within such algorithmic systems.

The persona-based walkthrough

The "walkthrough method" is a user-centered research framework proposed by Light et al. (2016), which combines STS and cultural studies perspective, aimed at comprehending how technologies like apps and platforms and their cultural references configure users (Duguay & Gold-Apel, 2023, p. 8). Following both Stefanie Duguay's walkthrough workshop suggestions, as well as Albrecht et al. (2019) article, we integrated the "walkthrough method" with the addition of "personas". This "persona-based walkthrough method" is situated within a virtual ethnographic method, and applied to analyze the affordances, discursive interface arrangements, data outputs and visualizations of the data infrastructures, as well as embedded cultural and discursive norms. The application's infrastructural elements are collected and analyzed according to the principles of the walkthrough method. Furthermore, we constructed diverse personas representing a range of demographic groups and minorities (e.g. ethnicity, gender) to navigate through data infrastructures, thereby illuminating the system's underlying assumptions (Marshall et al., 2019). This integration of personas with the walkthrough method is instrumental in revealing the intended purposes, embedded cultural meanings, and the assumptions about users and their interactions with the platform, application, or interface (Light et al., 2016). Once visible, we can scrutinize the infrastructures' hidden normative conceptions and biases within the socio-technical apparatus.

The primary data collection of the walkthrough method is twofold and consists of (1) an examination of the app's vision, operating model, and governance, and (2) a technical walkthrough. The first (1) part of the walkthrough method entails the analysis of two sources of information, the interface and the official documentation. An examination of the app's vision, operating model, and governance, discloses the purpose, target user base and scenarios of use of the HM (Light et al., 2016). The analysis of the operational model involves its business strategy and revenue sources, through which we examine the underlying political and economic interests. The analysis of the governance conversely involves all practices of regulation or management of user activity, in order to sustain their operating model and fulfill its vision (Light et al., 2016). Moreover, our analysis extends to the data visualizations generated by the Happiness Meter (HM) and its algorithmic operations. These aspects are examined through an (auto-)ethnographic component analysis, aligning with the second phase of the walkthrough method.

The second (2) part of the walkthrough method is called the technical walkthrough, where the researcher engages with the interface – focusing on things like the materiality and the physical interactions encouraged by the app – and walks through the app with an "analytical eye". The walkthrough method allows us to directly engage with the system's interface, enabling us to examine its technological mechanisms and embedded cultural references, as to understand how it guides users and shapes their experiences' (Light et al., 2016, p. 2). The method involves a step by step observation and documentation of an app's screens, features and flows of activity, whereby actions and interactions on an app become available for critical analysis. This observation process is contextualized by a review of the app's vision, operating model and governance. This review will reverse engineer the app's environment of expected use and its intended user, and thereby critically examine the workings of an app as a sociotechnical artifact (Light et al., 2016, p. 3, 6).

This paper enhances the methodological framework of the technical walkthrough by incorporating the use of personas, thereby introducing an additional dimension and focus in the system engagement process. Grudin and Pruitt (2002, p. 1) define "personas" as "the creation and use of fictional users, concrete representations". This methodological tool provides us with archetypical users, situationality and real world context. With the fictionalized setting of the personas as users, we can create coherent (sets of) input from imagined scenarios and partial knowledge, and insert these into the object of analysis (Grudin & Pruitt, 2002, p. 6). They allow us to go beyond the abstract representations of users, to imagine characters, goals and activity scenarios, and focus our attention on the design and use of the HM, that other methods do not.

Table 1. Description of personas

Source: Authors' own study.

	Name	Location	Gender	Age	Education
	Mieke Huizinga	Alphen aan de Rijn	Female	48	VMBO/MBO
	Alberto van Haren	Utrecht	Male	19	VWO/WO
	Henk Visser	Oost- Kappele	Male	72	VMBO
	Luca van der Horst	Westervoort	Female	30	HAVO/HBO

We have created two sets of personas: the "imagined user" which we hypothesize fit the system, and "anti-personas", which we hypothesize do not fit the system and thereby are suited to explore particular norms present in the system. In the creation of the (anti-)personas, we make elaborate use of the results from the first phase of the walkthrough method. The (anti-)personas were developed based on demographic data sourced from Statistics Netherlands (2018). All authors contributed to the creation of these personas, formulating not only demographic profiles but also biographies or narratives that encapsulate the essence of the data within a "foundation document". This document serves as a reference point for all data generated through the persona's application. Hereby, the persona characteristics will be explicitly linked to the input, and therefore output, data, making these ties salient (Pruitt & Grundin, 2003, p. 5). As such, the following (anti-)personas are constructed to enact the HM with its personalizable variables (Table 1 and 2).

Table 2. Description of anti-personas
Source: Authors' own study.

	Name	Location	Gender	Age	Education
	Virgil Dijksma	Bonaire	Male	38	HBO
	Robin Stevensen	Hengelo	Non binary	23	VWO/WO
	Erika Vaatstra	Rotterdam	Female	16	VMBO
	Lisa Medema	Groningen	Female	66	HAVO/HBO
	Michel van Bohemen	Nijmegen	Male	19	VWO/WO

The personas, representative of actual demographic groups as detailed in the preceding tables, serve to personalize interface variables and analyze score variations. This approach facilitates a critical examination of the contentious concepts and consequences inherent in the algorithm's computation of happiness scores. It aims to elucidate the algorithmic process underpinning the calculation of these scores.

Walking through the construction of a personalized happiness score

Following the analytical framework proposed by Light et al. (2016), our analysis begins with an evaluation of the HM's vision, centering its objectives, intended users, and usage scenarios, primarily conveyed through organizational documents, such as the *Welzijn in Nederland* report from CBS (2016). This document serves as a foundational piece for the HM, outlining its aim to educate the Dutch public on happiness metrics across three dimensions: evaluative (life satisfaction), emotional (positive and negative feelings towards life), and eudaimonic (perceived value of life experiences). These dimensions, as posited by the CBS, collectively gauge the Netherlands' well-being state, aiming to visualize this through the specified eight dimensions. However, the report does not elaborate on the rationale behind selecting these particular dimensions to represent the Dutch population's well-being. We draw from this document in relation to the visual components of the HM to demonstrate how the walkthrough is performed in practice. We start with visiting the homepage of the HM: the interface features a map of the Netherlands, highlighted by a circular visualization and a prompt button asking, "How happy is the Netherlands? Click here!".[7] The visualization incorporates a dynamic circular bar chart, symbolized by weather icons ranging from stormy to sunny to represent varying levels of happiness from negative to positive.

The user's interaction is limited to clicking a white button located in the bottom right corner, which reveals the Netherlands' average "happiness score" of 7.1. This, right away, sets an implicit normative assumption regarding the average level of happiness in the Netherlands and functions as a frame of reference. Then, users are prompted to discover the average happiness score for their respective provinces, guiding them to select their province for specific data. This action represents the sole navigational option within the interface. However, the system's limitations become apparent when considering users from special municipalities, such as Bonaire. Despite being officially part of the Kingdom of the Netherlands, residents of such areas, exemplified by the anti-persona Virgil Dijksma (see Table 2), are excluded by the system, highlighting a normative underpinning in its design.

[7] With all textual content translated by the authors.

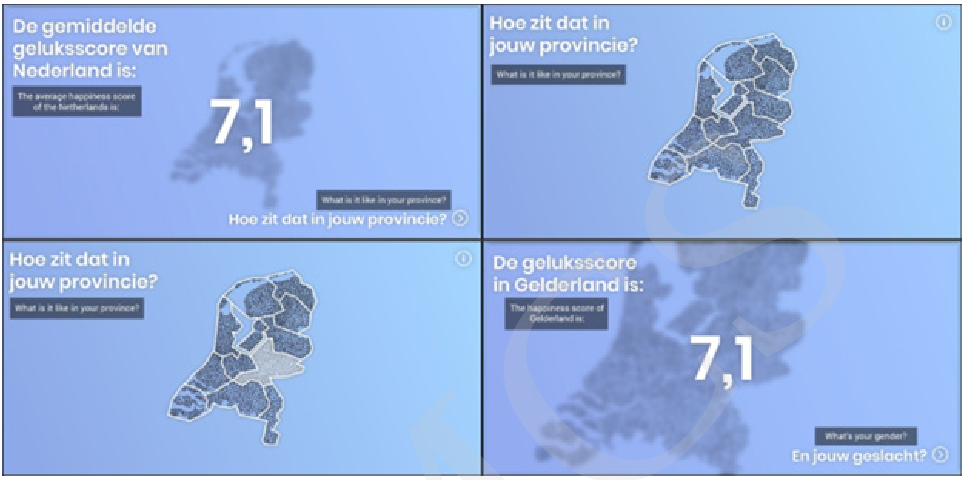

Figure 1.0–1.3. Display happiness score

Note. From top left to top right, to bottom left, to bottom right: (Fig. 1.0) The start page of the HM interaction saying that "The average happiness score in the Netherlands is 7.1. After clicking one is prompted with the (Fig. 1.1) province page which invites the user to select their province by clicking on it (Fig. 1.2), after clicking a province, the HM zooms in and displays the average happiness score of the region (Fig. 1.3).

Source: Authors' own study.

Next, the user has to specify their sex (Figure 2). A binary option is provided as the user can choose between male or female. Here, similarly as above, the interface forces the user to make a choice, otherwise the system denies them further access. In this way, the system enforces set norms on the user, contributing to user experiences that align with normative societal constructs. In this example, the HM reflects broader assumptions about gender, potentially shaping users' self-perception in relation to this demographic category. Again, we see one of our anti-personas drop out at this point, Robin Stevensen (see Table 2): a non-binary person, who does not conform to either gender.

The cisgender users that live in the twelve provinces of the Netherlands can continue using the system. Now, the user has to further specify their personalized happiness score by selecting an age group in which they are situated. The age groups consist of: 18–24, 25–44, 45–64, and 65+ (see Figure 3). It is not stated why an age group below 18 years of age is not incorporated within the application. This, again, reflects societal presuppositions regarding age in addition to the previous categorization of gender, potentially modifying users' self-image in regard to these categories. The only other interactive function is the "I" button on the top right corner of the screen. Clicking on this button shows a text which elaborates what the user has to do to continue in the system. This categorization makes sense for government datasets that focus on the working population, hence the exclusion of all under 18, it causes the exclusion of another anti-persona. Erika Vaatstra's (see Table 2) age group (<18) is not represented in the system – even though she recently graduated and got a job.

Figure 2.0–2.1. Gendered happiness score

Note: From left to right: (Fig. 2.0) The user is prompted to answer "What is your gender?". If in doubt, one can click the information button in the top right corner, which unfolds a window with instructions saying "click either the male or female icon". Through the hover animation, one is invited to click one of the options, after which the average happiness score of either Dutch males or females is displayed (Fig. 2.1).

Source: Authors' own study.

Figure 3.0–3.3. Happiness score depending on age

Note: From top left to top right, to bottom left, to bottom right: (Fig. 3.0) The user is prompted to answer "What is your age category?". If in doubt, one can click the information button in the top right corner, which unfolds a window with instruction (Fig. 3.1) saying "click the hourglass representing your age group". Through the hover animation (Fig. 3.2), one is invited to click one of the options, after which the average happiness score of either of the specified gender in that age category is displayed (Fig. 3.3).

Source: Authors' own study.

While the previous sections showed explicit norms through categorization, there are als implicit norms in the HM. Lisa Medema (see Table 2), is 66 years of age and still happily working[8] is put into the same demographic category as, for instance, Henk

[8] In the Netherlands, the official age of retirement is set at 67 years.

Visser (see Table 1), who is retired, resides in an elderly home, and lives a less active life. Obviously, not all people above 65 years of age have the same lifestyle – which seems to be the assumption in the system – even though lifestyle is a determining factor in how a person experiences life and happiness. The classification of individuals eligible for pension into a single category may be considered a presumptive and potentially flawed approach, because it overlooks the significant disparities in lifestyle and activity levels among this demographic, as exemplified by the contrast between Lisa and Henk. Such a blanket category limits the self-representation within the systems categories.

Subsequently, the user has to specify their personal characteristics by selecting their level of education (Figure 4). One can choose from the following education levels: elementary (basis), lower (VMBO), higher (HAVO/VWO), college (MBO), university (HBO/WO).[9]

Figure 4.0–4.3. Happiness score depending on educational level

Note: From top left to top right, to bottom left, to bottom right: (Fig. 4.0) The user is prompted to answer "What is your level of education?" through the hover animation (Fig. 4.1), one is invited to click one of the options, after which the average happiness score of one's gender, one's age group, and one's educational level is displayed (Fig. 4.2–4.3).

Source: Authors' own study.

[9] Within the Netherlands there are three levels of higher education: MBO (relates to community college), HBO and WO (which both relate to academic education, i.e. university. There is, however, a substantial difference between HBO and WO: HBO is an academic educational level for applied sciences, while WO is the highest academic level, or "the sciences".).

After this selection an average is given based on the user's personalization variables, and the HM first displays the highest and lowest values for your demographic, after which it shows the others as well (Figure 5). All of the eight dimensions are visualized within a circular graph. If you use your mouse to hover above the visualization, different scores are presented based on the eight dimensions.

Figure 5.0–5.3. Finalized happiness score calculation

Note: From top left to top right, to bottom left, to bottom right: (Fig. 5.0) The user is presented with the theme they are most satisfied about, after which (Fig. 5.1) they are presented with the theme they are the least satisfied with. Subsequently, (Fig. 5.2) all of the measures are displayed. Finally, (Fig. 5.3) the user is invited to fill out the questions themselves in order to calculate a personal score.

Source: Authors' own study.

The focus is on the "education and work" dimension, where users observe an average score of 8.0, attributed to highly educated men aged 45–64, who exhibit the highest satisfaction levels within this dimension. Should the user switch the gender to female, while maintaining the same age and education level, it is noted that women in this category express the greatest satisfaction within the "liveable surroundings" dimension. The methodology behind the calculation or visualization of these dimensions remains undisclosed, leaving users without the ability to delve into the data's underlying calculations or representations. This feeds into the understanding of the underlying algorithm as a black box, obfuscating how demographic data is used and translated into visual representations. The interface offers minimal interactive functionality, limiting users to a few selectable options for navigation and interaction within the system.

Figure 6.0–6.3. Personalized happiness score

Note: From top left to top right, to bottom left, to bottom right: (Fig. 6.0) The user is presented with an explanation of the interface. Subsequently (Fig. 6.1) the user can manipulate a circular bar chart to convey the amount to which they are satisfied with the question. The first time they do this (Fig. 6.2) the user is presented with a check screen to give them a feel for how the system works. After finishing all the questions, (Fig. 6.3) the user is presented with their personal score, which is compared to that of the average of their demographic.

Source: Authors' own study.

Civic normativity

The findings reveal critical insights into the underlying assumptions and biases in the HM, particularly how socio-technical systems like HM shape user experience and influence perceptions of well-being. By employing personas, especially "anti-personas", the study exposes civic normativity as dynamics of exclusions, such as gender non-binary users and people from certain geographic areas like Bonaire. These exclusions demonstrate the system's implicit civic norms, indicating a structured bias in how happiness is represented and measured. The HM's interface reflects broader assumptions about gender and age, potentially shaping users' self-perception in relation to these categories. The HM's structuring of "happiness" based on particular demographic and identity categories can also performatively shape user identities, echoing Hacking's (1986) concept of "making up people". This not only plays a role in shaping personal identities but also how society envisions demographic segments of happiness. This can be understood as an instance of data ontology, as discussed by Kitchin and Lauriault (2014), as certain normative categories imposed by the HM shape not just data outputs but also participants' lived realities by framing which identities and experiences are validated. This supports a broader critique of how socio-technical tools can become normative forces in society.

The rise of public-facing data interfaces, such as the HM, underscores an urgent need for improved data literacy among users and a heightened ethical responsibility on the part of the entities that design and disseminate these tools. Data literacy involves understanding not only how to read and interpret data but also recognizing the limitations, biases, and assumptions embedded within data visualizations and algorithms. When organizations provide data-driven tools for public use, they implicitly suggest that the metrics presented are objective truths; however, these "truths" are contingent upon the epistemological framing chosen by the developers and designers. This framing often reflects specific ideological and cultural values, thereby shaping users' perceptions and beliefs about complex societal issues – in this case, happiness. This can be understood as an instance of data realism (Kitchin et al., 2015), referring to the tendency to accept data representations as inherently factual or objective, which poses a significant epistemological challenge. Users may be inclined to view the happiness scores in the HM as concrete representations of social reality, largely because they are presented through the interface of a trusted public institution and framed in an ostensibly scientific manner.

This uncritical acceptance of data representations as "real" phenomena contributes to what Kitchin et al. (2015) call a "realist epistemology", where data is perceived as a direct mirror of society rather than a constructed representation shaped by selective parameters and algorithmic decisions. This data realism fosters a passive relationship between users and data, where users might accept the happiness metrics without questioning the methods or assumptions that underpin them. In the case of HM, this can lead to the perception that happiness is a universal, measurable quality and that the metrics shown are neutral representations of national well-being. However, this is misleading, as the happiness scores are based on predefined parameters (e.g. gender binary, limited age ranges) that exclude certain groups, thereby constructing a selective and biased portrayal of happiness in Dutch society. The epistemological challenge, then, lies in fostering a critical awareness that allows users to understand how metrics like these are crafted, what is included or omitted, and how the design choices reflect specific normative frameworks.

The position of the HM within governance structures might also be questioned, where it serves as an epistemic device influencing public policy. This positioning should be critiqued in relation to algorithmic governance, where systems of quantification shape public discourse around well-being and happiness, affecting individual and collective behavior (Gillespie, 2014). As shown, what people often perceive as objective mathematical entities, are in practice technologies driven by human choices – like categorization tables or decision trees, human observations and training data – embedding social inequalities, biases, ideologies and socio-cultural norms. The HM incorporates socio-cultural norms that have the potential to influence policy and citizens. Utilizing constructed anti-personas enabled the explicit demonstration of the system's embedded norms, thereby highlighting the exclusion of certain non-normative demographic groups. Therefore, we advocate using the persona-based walkthrough as a virtual ethnographic progression for user-centered research that focuses on the performative dimensions of socio-technical, algorithmic, data-assemblages like the HM.

Discussion and conclusions

In our analysis we aimed to answer the following questions: RQ1: How does the Dutch Happiness Meter (HM) embed socio-cultural norms and biases within its algorithmic design, and how do these translate to the quantification and representation of citizen happiness across diverse demographic groups?, RQ2: How does the persona-based walkthrough method reveal the limitations and exclusions of black-boxed e-government applications such as the Happiness Meter, and how can this method contribute to algorithmic accountability and transparency in digital governance?, and RQ3: What are the implications of datafying subjective well-being through tools like the Happiness Meter on public perceptions of happiness, and how does algorithmic governance influence the epistemologies of well-being in the context of policy-making and societal inclusion? With the novel methodological design of the persona-based walkthrough, we demonstrated how to contest the hidden and obfuscated norms built within data assemblages like the HM, and what its non-neutrality entails (Uricchio, 2017). By untangling cultural and computational synergies in our analysis, we examined their influence on civic normativity and quantified well-being. Our contribution shows how such data-driven systems construct a normative understanding of happiness which impacts governmental strategies and public accountability. The findings reveal critical insights into the underlying assumptions and biases in the HM, particularly how socio-technical systems shape user experience and influence perceptions of happiness and well-being.

Answering RQ1, through our findings we critique the narrative of objectivity presented by the HM, arguing that these systems obfuscate ideological biases behind technical design, especially the epistemological impact on how happiness is understood within public policy. The transformation of open government data into visual form, as seen within the HM, has similar problematic implications. By interweaving quantification and computing on datasets containing Dutch population demographics, the web application reproduces all sorts of opaque socio-cultural norms and values embedded in the datasets. Through these narratives of objectivity, quantification and visualization, these norms and bias present in both data and tool, are obfuscated, washed, and reproduced. This is also applicable to RQ3, and similar to the manner in which socio-cultural norms and biases on demographic groups were obfuscated, epistemologies of the subjective notions of happiness or well-being are made to be objective by the HM, and therefore become more potent tools for governance. The persona-based walkthrough method can scrutinize the way the HM refracts the subject-centered world by calculating a happiness score based on certain dimensions with normative measures. This shows the personalization variables within the interface, and thus potentially reshape and conceptualize the understanding and definition of happiness with non-transparent and unknown logics and formulas.

Answering RQ2, through the novel methodological design of the persona-based walkthrough researchers are enabled to study algorithmic black-boxed systems like the HM. And in regard to RQ3, data assemblages like the HM need to be scrutinized to unearth the algorithmic logics and a visual rhetoric of black-boxed e-government applications, which produce an exclusionary image of the Dutch population. As said, the poor representation and inclusion of disadvantaged or marginalized publics, and non-binary demographic groups within the HM is very problematic and should be addressed, but should in no way be considered as a small bias in an otherwise objective technology. It is important to consider the inherent characteristics and problems of data visualization technologies and how they are perceived and understood by the (general) public, with an average level of data-literacy. This holds even stronger for systems which attempt to measure and quantify qualitative aspects of our lived experience such as happiness. The non-neutrality of the data, the app, and the visualization are not communicated – even obfuscated – and so are all the ideological choices and presumptions that went into the HM. This means that the HM does not adhere to the demands for accountability.

The argument of Gillespie (2014, p. 4), that algorithms functioning as "talismans which imply objectifying scientific claims" is, thus, very much applicable here as it performs a kind of ideological work by presenting happiness as a computable and universally quantifiable metric. This framing problematizes the notion of neutrality and necessitates transparency in how values and biases inform algorithmic design. The HM employs a purportedly scientific methodology to compute a happiness score using statistical data, which it then displays through simplified, ostensibly objective data visualizations. This approach aims to quantify and objectify happiness in the Netherlands. However, the choices for the visualizations, dimensions, and indicators which construct the happiness scores/values are not motivated, and the scores are based upon surveys with a highly subjective character.[10] This is an example of the "parameterization", described by Drucker (2011, p. 128), where "data does not pre-exist

[10] Exemplary of this is the fact that the HM is running on statistical data gathered by the CBS in 2015, and has not been updated since. It is logical to think that the more time progresses, the older the data gets, and the value of the scores will decrease as it will less likely represent the current state of affairs within the Netherlands. This adds to the problematic notion of the HM, as it does not clearly specify that the calculated happiness score is based on data from 2015. Users could thus interpret the scores as a contemporary representation of happiness, and give a skewed perspective on the actual measure of happiness.

their parameterization", and that the translation from statistical data to visualization conceals this important notion.

Another way of investigating apps such as the HM is through a "social analytics" lens, which is a "phenomenology of how social actors and organizations with social aims appear to themselves, and to the world, under digital conditions" (Couldry & Powell, 2014, p. 3), or the everyday use and reflections on analytics (Couldry, 2015). This would require a lens away from the app and towards the interplay between the audiences it represents, the social actors that perform the analytics, and the response and adjustments of the audience to their social analytics (Couldry & Powell, 2014, p. 2). To address the risks posed by data realism and foster critical engagement with public-facing interfaces, there is a clear need for data literacy initiatives that go beyond basic data interpretation. These initiatives should aim to help users recognize the constructed nature of data and the implications of different design choices. The concept of data infrastructure literacy, coined by Gray et al. (2018), could function as a concrete step towards a relevant understanding of the epistemological challenges pervasive data infrastructures create. Within this research, we instigated to contextualize this understanding. We examined the HM according to this "new" perception of data literacy, arguing that the HM advances a narrowly conceived but powerful realist epistemology – society perceived through data as factual, objective and neutral – that is reshaping how people come to know happiness and govern society (Kitchin et al., 2015). Future research should explore how novel methodological frameworks, such as the persona-based walkthrough demonstrated in our study, can facilitate the examination and understanding of (semi-)governmental software applications within the context of emerging forms of data literacy. Virtual ethnographic method like the persona-based walkthrough that allow researchers to critique the epistemological dimensions of technologies such as the HM, should be paired with the responsibility to recognize our own "semiotic technologies" (Haraway, 1988, p. 579). For example, a limitation of the persona-based walkthrough is the reliance of method on the construction of fictitious personas, embodying marginalized experiences. As these personas are based upon real life profiles of demographic groups, these experiences cannot be dismissed as fictitious themselves. However, researchers can never fully "think with" and/or "take on the perspective" of the constructed personas (Haraway, 1988). This distance to the personified individual should be made explicit and acknowledged by the researcher. As Duguay and Gold-Apel (2023) suggest, for analyzing the practices of non-normative, unexpected, and therefore underrepresented users, their situated knowledges (Haraway, 1988) are required.

In conclusion, the HM's operations and visual outputs craft a narrative for the public, both as a collective and on an individual level, suggesting that complex and extensive data repositories are being made understandable to them, a notion critiqued by Kitchin et al. (2015). We should not expect that this "explanation of the self" is easy to dispute, as argued by Haraway in her famous plea for responsible representation in epistemological devices (Haraway, 1988, p. 585). Subjects, exposed to the compelling visual rhetoric of data visualizations, interpret their identities through these representations. Additionally, their portrayal as subjects within CBS datasets is also leveraged by governing institutions. When Kitchin and Lauriault (2014) describe Hackings' (1986) scheme for the occurrence of a *data ontology* – illustrating how the bureaucratic processes of classification and categorization, through their inscription into datasets, are not merely descriptive but performative, effectively constructing a data ontology. Thus, as data-driven systems increasingly mediate our understanding of complex social issues, data literacy becomes a form of civic empowerment. It allows individuals to question and challenge the representations of reality offered by socio-technical systems, fostering a critical consciousness that can resist simplistic or exclusionary narratives. Without such literacy, systems like the HM risk entrenching certain normative views of happiness that exclude or marginalize non-normative identities. By promoting data literacy, we not only equip individuals to understand data critically but also empower them to participate actively in shaping the narratives that define their social world.

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