Context-Sensitive Assessments of Human Wellbeing

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ABSTRACT

My Wellness Check is a wellbeing assessment system designed to support information feedback loops within large organizations. The system was designed to help a technical university understand and respond to the needs of its students and staff during the COVID19 pandemic. In this paper, we describe the human-centered design process used to develop this context-sensitive wellbeing feedback system. We share findings from the first feedback cycle, where the assessments were sent to over 30,000 students and staff and used to inform community action. We were successful in informing responsive action at an institutional level and our approach highlights the need for context-sensitive measures of wellbeing in complex systems.

KEYWORDS

context-sensitive measures, wellbeing, digital environments, covid-19

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1 INTRODUCTION AND BACKGROUND

Artificial intelligence (AI) is changing our world by automating the process of optimization. Nearly anything can be optimized through computational methods, from the effects of novel drugs to the effects of new interface designs. AI is vastly increasing the number of outcomes that we *could* optimize, yet it remains a moral question of what we *should* optimize. Although scientists are often reluctant to engage in moral questions, in The Moral Landscape, philosopher Sam Harris makes a strong case for the "science of morality"[7]. He describes the philosophical position that moral values must be based upon "facts about the wellbeing of conscious creatures"; this opens up the potential for engagement between morality and science because facts about wellbeing are suitable for empirical inquiry. Further, this perspective helps address the moral question of what AI systems should optimize for: the maximization of wellbeing[1]. How might we, then, design AI systems to optimize wellbeing?

Artificial Intelligence (AI) is a rather vague term that can be applied to a large number of technologies, old and new, from deep learning neural networks to simple logical algorithms. One clear definition comes from Peter Norvig, the director of research at Google, who defines intelligence as 'the ability to select an action that is expected to maximize a performance measure' [13]. This definition frames three components that are essential for intelligent systems: a range of possible actions, measures of performance, and an action selection procedure based on a model of maximized performance. For our purposes, moral AI should adopt measures of performance based upon wellbeing.

1.1 Success metrics

Today, platforms like Facebook and YouTube tend to maximize more easily accessible measures like time-on-site. These platforms are powered by AI technologies that select actions — such as video recommendations — that are designed to keep people engaged and watching. In the case of YouTube, this can lead to relevant algorithms optimizing for outrageous content — not by design, but because outrage fuels time-on-site. Time-on-site is easy to measure and it contributes to corporate monetization goals. Why don't companies aim to optimize human wellbeing? In a 2016 TED talk, Tristan Harris highlights one reason for this very clearly: "[I]magine dating services, like Tinder, where instead of measuring the number of swipes left and right people did, which is how they measure success today, instead measured the deep, romantic, fulfilling connections people created." In this example, the existing metric – number of swipes left and right – is easy to measure, while the alternative – fulfilling romantic connections – is not. What this illustrates is the difficulty of translating human values into feasible metrics. Regarding the topic of wellbeing, the same questions arise. Let's say we want a powerful media streaming platform to cease optimizing for time-on-site but rather for wellbeing. Then, what might that be? Happiness? Life satisfaction? Mental health? And further, how do measure these factors? This notion puts forward one major challenge for the design of AI for Wellbeing, that of measurement, for which we need suitable measurement instruments [3].

[1] "That action is best, which procures the greatest Happiness for the greatest Numbers; and that, worst, which, in like manner, occasions Misery" (1725;1973, Francis Hutcheson, Inquiry concerning Beauty, Order, Harmony, and Design, II.III.§VII)

1.2 Value alignment

In 2020, Deep Mind published an extended consideration of the challenges of embedding human values into AI systems [6]. They describe the importance of value alignment in AI and show that this is equally challenging in purely human systems. "Behind each vision for ethically-aligned AI sits a deeper question. How are we to decide which principles or objectives to encode in AI—and who has the right to make these decisions—given that we live in a pluralistic world that is full of competing conceptions of value?" To help address this question, we consider how human-centered design methods — particularly community-led methods — enable the discovery and integration of the needs and values of diverse stakeholders. What is needed, then, are methods that can extend these design methods to support the measurement or assessment of those diverse values, over time.

1.3 Cybernetics

We suggest that a "cybernetics perspective" can be especially helpful in human-centered AI work as the term naturally accommodates a broader, systems-level viewpoint. For instance, consider the notorious "autoplay" function used by Netflix and YouTube. By automatically playing the next episode within seconds of completion, autoplay is well known to maximize outcome metrics like time spent. However, autoplay is a UI-element — it is not part of the recommendation algorithm that tends to be the focus from an "AI perspective." A "cybernetics perspective", in contrast, may more easily recognize non-algorithmic factors used by systems to maximize performance measures: visual design, interface elements, even content production, and human decision-making. As the broad societal concern with AI is not limited to algorithmic details but the overall impact of data-driven systems, cybernetics seems to offer a valuable intellectual foundation and source of systems-level theoretical constructs for designers [1]. It is from this cybernetics perspective that we envision how we can learn from the integration of wellbeing in complex human systems in order to design digital environments that can acknowledge new vulnerabilities and empower people.

In this paper, we discuss a case that highlights the importance of context-sensitive wellbeing measures for complex systems to be adaptive to new vulnerabilities that arise from unfamiliar contexts — such as the COVID-19 crisis — and from a cybernetics perspective extend the importance of our findings to the development of digital systems that can both acknowledge vulnerabilities, but most importantly, are able to empower people. First, we will shortly discuss the relation between AI and Cybernetics. Then, we will address the need for context-sensitive measures for the assessment of wellbeing of students in times of COVID-19. Lastly, we will discuss the importance of our findings for the development of digital environments.

2 CASE STUDY: INTEGRATING WELLBEING FEEDBACK IN UNIVERSITY SYSTEMS

The purpose of our work was to integrate wellbeing feedback into a complex human system. We conceived this as a cybernetic loop that can assess wellbeing and inform responsive action, see Figure 1. Our goal was not just to create a system for measurement but to create a feedback system capable of informing the actions of a large university during the COVID-19 pandemic. Creating change in Universities is difficult due to their size, complexity, diffuse management structure, and their tendency for consensus-based decision-making. The challenge of designing for large, complex socio-technical systems has been described by Norman and Stappers as DesignX problems [10]. As large, overarching plans have a tendency to fail, the authors advocate for a formal method known as "muddling through": small, incremental changes at many levels of the organization. We hypothesize that cybernetic feedback, such as our context-sensitive wellbeing assessments, may support this "muddling through" process in several ways. These measures can help various organizational stakeholders to 1. understand the nature of the problems, 2. prioritize these problems and solutions, 3. help communicate the problems broadly (so as to support uncoordinated, bottom-up organizational responses), 4. inspire novel ideas for solutions and, eventually, 5. determine the efficacy of solutions.

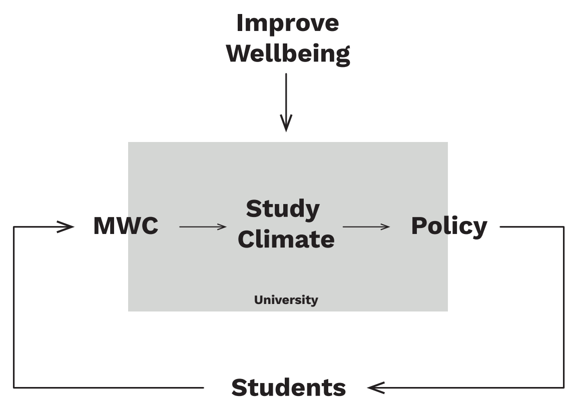

Figure 1: A schematic depiction of a cybernetic loop that can assess wellbeing and inform institutional responsive action. MWC refers to the wellbeing assessment instrument dubbed 'My Wellness Check'

2.1 Need for Contextualization

In a news article, Dr. Nicole Crawford expressed that in order to support student wellbeing in these trying times, it is important to understand student needs [9]. She states that: "Your students may be juggling parenting and work with their university studies, as well as becoming home-school teachers (overnight), and coping with the stressful and anxiety-provoking environments in which we're now living." In other words, assessing wellbeing in an unfamiliar situation — such as a global pandemic — might require the use of novel, context-sensitive measures, in addition to validated measurement of psychometrics. To construct these measures, it is then necessary to understand your research population — the community — and the different elements that they are juggling. Further, Gabriel notes a philosophical challenge that underpins the alignment of AI to values, is that researchers should aim to identify values that can be adaptive to change [6].

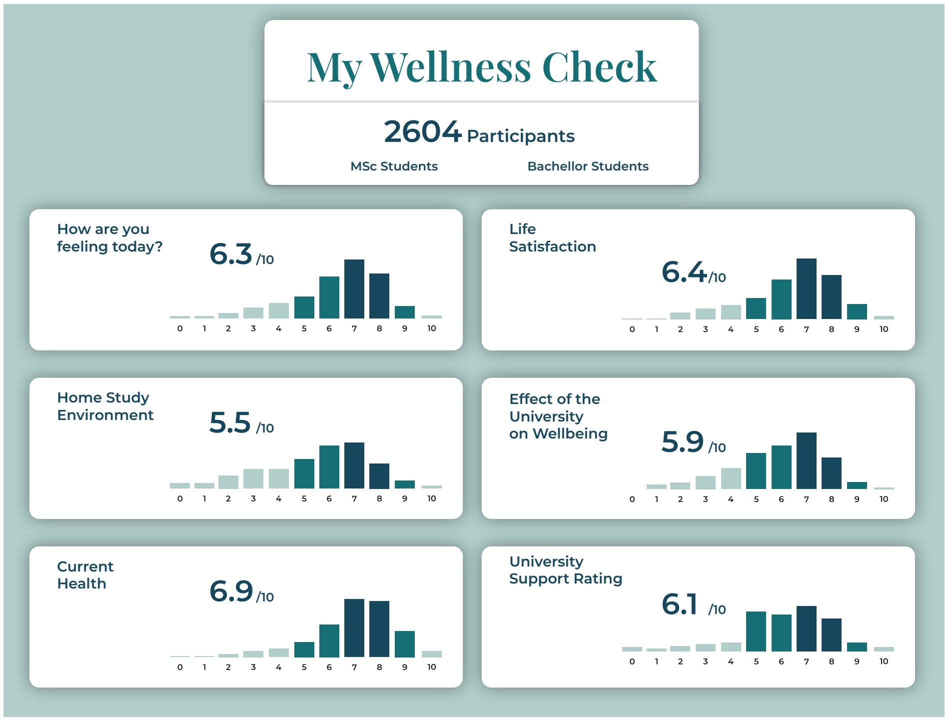

Figure 2: An image showing the distribution of scaled items of My Wellness Check for students as communicated back to the research population.

Table 1: A regression model (r squared = 0.64) of "Life Satisfaction" showing the predictiveness of survey items demonstrating a p-value <0.5 .

Source	*FDR LogWorth*	*PValue*
How are you feeling today?	48.812	<0.00001
I often feel lonely	15.626	<0.00001
During the past study term, how satisfied were you with your physical study environment at home?	15.168	<0.00001
Rate your current physical health	13.633	<0.00001
I am generally optimistic about the future	11.264	<0.00001
overall, I often felt down	10.109	<0.00001
I often feel disconnected from my family	3.67	0.00021
I'm part of a student association	3.518	0.0003
Overall, what effect has the Coronacrisis had on your study motivation?	3.502	0.00031
I am satisfied with my study / life balance	2.85	0.00141
overall, I felt good about my sleep	2.831	0.00148
How worried are you about your financial situation?	2.233	0.00585
—— has been responding appropriately to the Coronacrisis 24	2.113	0.00771
I believe I have been discriminated against at ——– due to my ethnicity, gender, sexual orientation, etc	1.597	0.02529
my study place is not ergonomic and I can feel the negative effects	1.537	0.02903
I am happy with how I am performing in my studies	1.486	0.03264

Thus, with regards to an unfamiliar context, such as a global pandemic, it might not be adequate to merely consider *off-the-shelf* wellbeing assessments such as the Satisfaction With Life Scale [4]. Rather, an understanding of what *should* be assessed must be developed. Therefore, to establish appropriate measures to inform a wellbeing feedback loop, stakeholders and those most impacted had to be included in the development of our assessment instrument. Practically this entailed the involvement of community members in the form of workshops to design the survey [8, 11, 12, 14].

2.2 Summary of Results

The results (Figure 2) show that student life satisfaction was at the global average level of around 6.5 on a scale of 0 to 10 [5]. This is about 1 point lower than the Dutch average [5]. This is likely due to the fact that this study was conducted during a pandemic as other studies reported a decrease in life satisfaction as well e.g. [15]. From a regression model (Table 1) predicting "Life Satisfaction", we observe that mood has a disproportionate influence on Life Satisfaction, as expected[2]. Loneliness and satisfaction with their physical study environment at home are the next most predictive factors in student wellbeing. This finding is surprising, as one's physical study environment is not a typical factor used in studies of subjective wellbeing; this demonstrates the value of using insights from our human-centered design process to create a context-sensitive assessment. We anticipate that this relationship between the home study environment and life satisfaction will substantially diminish post-pandemic.

2.3 Discussion

The assessment revealed many other factors associated with student wellbeing, including physical health, optimism, depression, family connection, participation in student associations, sleep, finances, discrimination and study performance. It is difficult to determine the causal relationship between these factors and life satisfaction; nevertheless, the regression model helps to provide a relative prioritization of student needs for addressing by the university.

The case study showed that in order to create wellbeing feedback loops that inform successful system action, it is advisable to consider a designerly approach to the construction measures that fit the context. The paper communicated an approach to identifying and constructing measures that were appropriate to the specific context. The results that ensued further highlight the need for context-sensitive wellbeing measures. This refers to the fact that traditional off-the-shelf instruments would both not have picked up on factors that are *currently* highly indicative of one's wellbeing – e.g. student's home study environment – and that they are not always as informative for action – e.g. how does one respond to decreased life satisfaction scores? In line with this example, the question then remains to what extent these contextual measures are reliable for the assessment of wellbeing, especially in the long-term – e.g. will a student's home study environment still be indicative of their wellbeing when the pandemic is over? The reliability of contextual measures should be further explored in two directions, theoretical and empirical.

2.3.1 Limitations & Future work. First, a student's *home* study environment might become less important after the pandemic, but their *study environment*, in general, can still highly indicative of their wellbeing. Context-sensitive measures should be able to be pick up on current *manifestations* of wellbeing. In other words, contextual wellbeing measures can be very specific indicators for higher-order wellbeing phenomenon which can be indicators for their reliability. This notion requires further theoretical exploration.

Secondly, context-sensitive measures that are unique to a given context should be validated empirically — be it a measure responsive to a consequence of a global pandemic or one that is based on an interaction that is unique to, for example, a social media platform. This would require a sufficient number of iterative assessment cycles that include interventions designed to improve the phenomenon associated with that specific measure. Therefore it is recommended that future research geared towards the identification of context-sensitive measures and the empirical testing of the reliability of these measures should be with platforms that allow for short iterative cycles.

3 CONCLUSION

This paper has investigated methods for integrating human wellbeing feedback loops within cybernetic/AI systems. We introduced a contextually-sensitive design process for creating wellbeing measures within a large university during the COVID-19 pandemic. Our main findings validate the importance of contextualizing wellbeing measures; for instance, ratings of home environment have not been a major factor in theoretical models of wellbeing, yet they were one of the most predictive factors in our model. Thus, in order to "design digital environments in a way that acknowledges vulnerability but also has the potential to empower people in ways that are meaningful for them," it is advisable to adopt a cybernetics perspective and construct context-sensitive measures to inform the design process and optimize the system.

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