3 I spy, with my little AI

How queer bodies are made dirty for digital technologies to claim cleanness

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The year 2017 was a pivotal year for conversations around Artificial Intelligence (AI), gender, and sexuality. In their much reviled and heavily criticised experiment at Stanford University, machine learning and data scientists Michal Kosinski and Yilun Wang, trained machine learning algorithms to create a "sexual orientation detector" using 35,326 images from public profiles on a US dating website. They created composite faces, using an aggregate of images from self-identified straight, gay, or lesbian profiles, and claimed that based on this, their algorithm can now detect people's sexuality with "more accuracy than human beings" (Kosinski and Wang 2017).[1]

Their academic article is perhaps less ambitious and suggests that the AI, when compared to a data set of human detectors inferring sexuality by looking at a picture, is 81% of the time more effective at distinguishing between gay and straight men and 74% of the time for women. The media uproar that followed this claim was proportionate, both in the rejection of this claim as well as in warning against the weaponisation of AI technologies to even attempt such an experiment (Vincent 2017). Several authoritative voices spoke out against this experiment and its claims, with activists from gender and sexual advocacy groups as well as scholars from their own disciplines, debunking their experiment, showing the fault lines of their data sampling, revealing the biases of their analysis, and marking the latent queerphobia and heteronormative biases that are present in this research, which received huge attention because of the media that amplified it and the academic institute that housed and supported it (Levin 2017).

The Human Rights Campaign (HRC) and GLAAD immediately labelled this as "junk science" and reminded us that the idea of a "gaydar" and reducing human sexuality to perceived characteristics is both "dangerous and flawed." Ashland Johnson, the director of public education and research at the HRC, said in a statement,

> Stanford should distance itself from such junk science rather than lending its name and credibility to research that is dangerously flawed and leaves

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> the world – and in this case, millions of people's lives – worse and less safe than before.
>
> (Anderson 2017)

Blaise Aguera, Alexander Todorov, and Margaret Mitchell (2018), while still expressing concerns about the ethics of such work, were even more worried about the fundamentally wrong experimental setup as well as the basis for the claims that Kosinski and Wang were making. In their long essay on *Medium*, they warned that the kind of work Kosinski in particular was pushing for, was regurgitating the "junk science of physiognomy (which) has roots going back into antiquity, with practitioners in every era resurrecting beliefs based on prejudice using the new methodology of the age" (ibid. 2018). In their essay, they focus on the science to quickly show that Kosinski and Wang were dishonest in the kind of input they were giving to the AI algorithms, and were wilfully and dangerously blind to the contexts within which our sexuality is both performed and perceived. They conclude that Wang and Kosinski

> [b]elieve that the chief differences between their composite images relate to face shape, arguing that gay men's faces are more 'feminine' (narrow jaws, longer noses, larger foreheads) while lesbian faces are more 'masculine' (larger jaws, shorter noses, smaller foreheads). As with less facial hair on gay men and darker skin on straight men, they suggest that the mechanism is gender-atypical hormonal exposure during development. This echoes a widely discredited 19th century model of heterosexuality, 'sexual inversion'.
>
> (ibid. 2018)

Responding to another non-peer-reviewed study initiated by the Chinese government claiming that they had trained a face-recognition algorithm to predict, with 90% accuracy, whether someone was a convicted criminal, Aguera et al. (2017) had also warned that "developments in artificial intelligence and machine learning have enabled scientific racism to enter a new era," something that they saw being consolidated in the production of the AI Gaydar.

Sarah Myers West, Meredith Whittaker, and Kate Crawford in their considered report on *Discriminating Systems* (2019) show how predictive AI is not just flawed in its predictions but ontologically wrong in its very existence. AI that is modelled around studying physical appearance as a proxy for character is darkly resonant with the history of "race science" and, in particular, "the debunked field of phrenology that sought to derive character traits from skull shape and was invoked by white supremacists in 19th century America."

The basic problem with Kosinski and Wang's experiment is that it did not just build tools that others can now use to do queer detection, but it is also supported by homophobic assumptions about gender and sexuality. As Sociologist Greggor Mattson (2017), in an exhaustive decoding of both the implied heteronormativity and the sinister intent of this experiment, notes, "what's creepier than Kosinski's flawed algorithmics is his naïve confidence in the moral and political neutrality of science."

Jeremy Howard (2017), with *Fast AI,* perhaps offers the best conclusion to this saga, when he points out that Kosinski and Wang have not necessarily developed a new technology. They have merely exploited the correlation and pattern-detection capacities of highly resourced AI algorithms, trained them on a flawed dataset, and fallen into the cardinal trap of confusing correlation with causation. And yet, the militant insistence on its accuracy and making this set of tools more widely available means that they have empowered queerphobic societies to get on AI-driven queer hunting backed by faulty modelling and analysis. Howard says with resignation, "It is probably reasonably (sic) to assume that many organisations have already completed similar projects, but without publishing them in the academic literature."

A lot of attention and public discourse in the face of these AI-queerness detection problems has been about the ways in which existing homophobia and gendered and sexual violence is being resurrected through these new technological implementations. The critics and advocates have ardently shown us how the scientific principles and the technological deployment are both flawed and need to be heavily reconsidered for the future. These critiques and interventions are valuable, urgent, and need to be celebrated for pushing back against the unholy nexus of heteronormative patriarchy and militarised technologies that seek to persecute the noncanonical bodies and identities with their weaponised AI.

For this chapter, I want to focus on something that seems to not be a part of these conversations, which is the construction of queerness itself, in the growth and expansion of AI-driven systems. I add to this discourse the proposition that the cases like Kosinski and Wang are not just about mobilising, catalysing, or detecting sexuality, but about constructing it in specific tropes that persist long after the initial anxiety about the immediate implementation has faded. I am suggesting that at the heart of the problem here is that AI and queerness are often thought of as separated—one being the site of operation for the other—where they should really be thought of as co-constitutive. I propose that we look at the AI-Queerness relationship not through the teleology of detection or the ambition of preservation, but through the ontology of how each is constructed through the other and how we need to break through this pattern.

Detective AI

There is a long-standing history between queerness and technologies of detecting queerness. Technologies of detection compete with the narratives of "coming out." The agential, empowered, self-identification move that puts the queer person in control of their narrative and practice, gets replaced by technologies of detection that have been invested in "outing," thus making the person vulnerable and assigning and public gender and sexual identity to a person without their information and certainly without their consent.

The idea that queerness is something that has to be detected and identified is not new. As Gregory Mattson pointed out,

> 19th century measurements of lesbians' clitorises and homosexual men's hips, to late 20th century claims to have discovered 'gay genes', 'gay brains', 'gay ring fingers, 'lesbian ears', and 'gay scalp hair' have all been ways by which historical technologies have been used to dehumanize and persecute sexual minorities under a scientific pretext.
>
> (Mattson 2017)

There has been consistent investment in figuring out a queer person, weaponising technologies to detect, control, monitor, and punish what was considered as deviating from the arbitrary norm of sexual identities of the times. Digital technologies have not been innocent and have long been implicated in structures of outing and detection, often justified by arguments of public health, safety, and care.

One of the most urgent examples of this is in the emergence and recognition of Monkey Pox as a global health concern in 2022. As the world is just recovering from the global lockdowns catalysed by the Covid-19 pandemic, there is obviously increased scrutiny around new patterns of contagion and public health. In the epidemiological reports and studies, it clearly shows that Monkey Pox has a rate of incidence which coincides with "diminishing herd immunity against the *orthopoxvirus* species" (Grant et al. 2020). However, as the virus spreads in different parts of the world where it is not endemic, there is an increasing labelling of this virus as a "gay disease" (Parrilla 2022). While more incidents might be reported in men having sex with men, there is no doubt that this is a universal problem and is spread through close contact, and not necessarily through sexual activity. However, the AI-based targeting on gay dating apps has already started addressing and educating gay men as the potential carriers and as high-risk populations (Caledron 2022). Thus, Grindr, one of the most popular gay dating sites started sending warning messages to queer men in Europe about the dangers of Monkeypox because it "appears to be more prevalent in networks of gay and bisexual men" (Wakefield 2022). AI modelling that identifies queer people is targeting them as high-risk and thus nominating them for early vaccination.

Alexandra Juhasz and Ted Kerr (2014), in their exhaustive analysis of the HIV/AIDS pandemic, call this the "larger media ecology of AIDS," which includes more than just the data and its analysis. The foregrounding of queer people as at-risk also leads to further modelling where the contagion data primarily focuses on queer sexual practices, leading to a self-contained feedback loop where the queer body is cared for the most, and hence also studied the most, creating automated results that insist that the infection like Monkeypox is necessarily a gay disease, with queer bodies as immediately suspected of being vectors of contagion. Cait McKinney (2022), doing a digital archival history of HIV/AIDS activism, reminds us that "AIDS activists understood and used networked computing, when it was new, as an essential tool for organising and rapidly communicating health information within precarious conditions." However, it is also important to realise that these informational sets, when opened up to machine learning networks, and especially dubious studies like those of Kosinski and Wang, might eventually come up with correlations that it is indeed the homosexuality, which leads to the queer bodies as "dirty" and "contagious." The detecting AI is not trying to detect the queer body, but to detect it as dirty, and reinforce the idea of the dirty queer through this modelling.

The idea of this dirty queer body plays out in many different narratives of social, political, cultural, and technological contamination. Politically, in Russia, when the country was mobilising to ban gay marriages, LGBTQIA+ members using digital dating apps like Tinder were actively harvested of their data, including messages and pictures, which were stored on local servers, leading Tinder to introduce a new feature called "Traveler Alert," that uses their location to warn users when they enter a region where their very presence might be considered a crime (Locker 2019). Similarly, the easy peer-2-peer connectivity and algorithmic matching offered by gay dating apps has led to an increased number of "gay hunters" (Fitzsimons 2019), which allow people to pose as queer on certain websites, match with prospective dates, and then crowdsource them on "a website that encourages to 'hunt' LGBTQ activists, inspired by the torture-themed film 'Saw'" (ibid.).

Socially, we see reports of how AI is trained on specific data sets of sex offence registries in the US, to come up with automated labels for young queer people as "deviant" (Wahl and Pittman, 2016). Queer people are driven towards self-harm and often caught in a filter bubble of depressive information on algorithms that keep them trapped there to increase profits and engagements. Culturally, the recent whistle-blowing testimony of Frances Haugen to the US Senate clearly demonstrates that young women and queer people were directed towards self-harm and depression on platforms like Facebook and Instagram (Haugen 2021) and this is amplified by algorithms which tagged them as queer and started pushing them towards specific kinds of behaviours (Leufer 2021). Technologically, we saw how the popular car-sharing taxi service Uber, rolled out a Real-Time ID Check that uses facial recognition systems which immediately locked out trans drivers (Urbi 2018), because the system was not capable of recognising and managing transitioning faces (Brammer 2018). Sasha Konstanza-Chock's brilliant thesis on "Design Justice" (2018) has already shown how AI-driven models of gender and sexual normativity target and punish trans-people going through the security devices on airports, subjecting them to greater scrutiny and harassment because their bodies are identified as atypical or "deviant."

This list is more symptomatic than exhaustive, more exhausting than inspiring. It does, however, establish my basic argument, that there has been a continued reproduction of the queer body as dirty, and that the detecting technologies have always focused on identifying, not just the queer body, but its particular strain of dirt (as an attribute or an explanation for its practices) which can be further managed, exploited, or weaponised. My proposition is that Detective AI is not really just about outing queer people or even trying to protect them by identifying them as high-risk. Instead, we need to read them as deeply complicit in the construction of queerness as contaminated and unclean, and they do that in order to present themselves as clean and robust, thus refuting the increased scrutiny of how they are leaking, hacking, and sharing information and data about the users, without their consent, in a web of unethical practices.

Clean AI

One of the keenest promises and biggest myths of digital technologies is cleanliness. There is a continued insistence of how digital systems are clean, reliable, and designed to avoid unwanted contamination. Particularly with AI, which is also seen as an evolution of legacy digital systems of computational networks, the rhetoric is prominent. In e-governance, where AI-driven systems are seen as the epitome of the SMART (Simple, Moral, Accountable, Responsible, Transparent) principles, we encounter the idea of AI as incorruptible and hence able to manage and control the corruption in our messy social structures. In our work monitoring and comparing the AI and governance landscape in India and Japan, we have seen both the countries develop national AI strategies. Elonnai Hickock and Vincent Zhong point out that

> In 2019, Japan published the Integrated Innovation Strategy Promotion Council and adopted the seven Social Principles of Human-centric AI and the 10 R&D and Utilization Principles of AI for developers. In 2021, Niti Aayog, the public policy think tank of the Government of India, published a set of six 'Responsible AI' principles to guide the development of AI ecosystems in the country.
>
> (Hickock and Zhong 2022)

They quote from Niti Aayog's paper to see how these AI principles are expected "to be grounded on the nation's accepted value systems and compatible with international standards," while the Japanese research suggests that "we should respect the following three values (dignity, diversity and inclusion and sustainability) as our philosophy and build a society that pursues their realization" (ibid.). However, there are two key tropes worth noting here. Both the frameworks very clearly accept the existing norms and values as the ones that will be used to measure the work and development of AI.

The goals are presented as technology-neutral, as if the existing or future technologies are not already shaping and shaped by these values. Additionally, while AI is meant to be informed by these human values, it is also clear that the role of AI is, in fact, to measure these social values. Thus, in a country like India, where positive gay rights are still absent, the good governance AI is not going to be deployed to further the rights of queer people but will in fact be used to maintain the status quo. The insistence on contextually appropriate ethical frameworks means that the ethics that form the context for the emergence of these AI are already seen as normative, and the role of AI in governance is to ensure that these get maintained and enforced, because AI is seen outside this fold, and hence better positioned to override the human messiness in these contexts. As Chinmayi Arun (2019) explains in her evaluation of harms, discriminations, and exclusions that emerge out of bad data design, AI is only as good as the data set that it is trained on. She writes,

> The very design of data sets can be biassed as a result of assumptions and gaps. The datasets could under-represent or wrongly represent certain populations, leading to discrimination against them or to their exclusion. Even if the dataset is accurate, its structure can end up discriminating and marginalising people; the classic example being datasets that code people as either male of female, erasing other forms of gender identity.
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> (Arun 2019, 10)

Following Arun's argument, it is clear that while the development and intention of AI might be aligned to these human-centric, AI for social good principles, the presentation of AI as free from the existing biases and prejudices is futile. As Kate Crawford and Jason Schultz (2019) point out, this separation of AI from the context of its operation is a strawman argument that presents AI as clean and good, and capable of correcting the corruption and mal intention of the human actors.

In technological settings, either with the global alliance in AI or with one of the largest AI for Social Good projects pioneered by Google, these problems remain fraught. Timnit Gebru, one of the co-lead of Google's ethical AI team, announced in 2020 that she was being forced out of her job. Karen Hao (2020) reports that Gebru, who had already authored a pathbreaking paper that showed that machine learning facial recognition is less accurate at identifying women and people of colour, had come up with another paper that was being silenced by the head of Google AI. Gebru's collaboratively researched draft paper, which eventually got leaked online argues that large language models that are trained on exponentially increasing amounts of text from the internet are at risk of amplifying racist, sexist, and otherwise abusive language (Simonite 2020). While this in itself is not new, they show that these AI, trained on older text models, would be unable to account for, accommodate, or operationalise new languages, vocabularies, and expressions of diverse communities, and will always treat them as deviations. Thus, anti-sexist, anti-racist, and trans-positive languages which play with pronouns, new identities, and forms of solidarity will automatically be considered as "wrong" by these AI, which will then take it as an example of some communities perpetually being wrong and in need of correction.

The affirmation of cleanliness is both an exercise of control and a black-boxing of technologies, despite the fact that we witness how computational technologies are ontologically and manifestly produced through multiple layers of contamination. A cursory look at algorithmic governance practices opens up a field of intentionality, bias, encoded discrimination, and amplified filtering that lead to the production of harm and violence without accountability and restitution (Chiu 2018). The obsolescence of databases, leap-frogging of technologies, and continued breaches and leaks of data and information belie the idea of immortal data and indeed present data and information infrastructure as fragile and prone to breakdown and manipulations. Especially in the world of self-learning algorithms and networks of correlation, we see our reliance on unexpected, undesigned, and unplanned-for variable queering models, producing states of exception, and leading to designed deviance which can neither be planned nor controlled.

Cleanliness, then, is neither an attribute nor a condition of digital networks and their spaces. The foregrounding of cleanliness has to be seen as an attempt to clean bodies, information, data sets, and approaches that threaten the power, destabilise the status quo, and resist the benign narrative of computation that is being naturalised in our everyday practices of digitisation. Cleanliness has to be recognised as an active way by which resistant data and technology usage—queer data and usage—can be controlled, punished, and penalised in order for dominant narratives to be favoured.

The detective AI technologies, based on their predictive models, present a certain narrative of cleanliness to create the dominant aesthetic of our computational times that reinforces this filtered, curated, cleaned digitality as the de facto mode of visualising and engaging with the digital. The construction of the dirty queer has to be seen in conjunction with this presentation of clean AI (Nenad et al. 2021). The conversation and the co-constitution of queerness as dirty and AI as clean is deeply intertwined, to an extent where we could argue that for AI to be clean, queerness will have to be dirty, and that the modelling and deployment of AI exploits the terrain of queer bodies, voices, practices, and phenomena to reinforce itself as clean in the face of undeniable data that these technologies are messy, leaky, and violently militant in their everyday practice.

Queering AI

The continued reproduction of cleanliness and dirtiness, as attributes of AI and queerness respectively, seems to be inescapable. The rhetoric of AI development as necessarily improving the human condition, but particularly removing the "unwanted" or "undesirable" structures of contamination and corruption, inevitably frames queerness as a site of detection, management, containment, and punishment, thus falling in a long legacy of technological refusal to recognise it as a legitimate subculture of lifestyle, and measuring it always as an aberration (Halperin 2014). Even when AI-driven implementations are geared towards developing queer alternatives and intentions, the ontological presumption of detection and removal, at the level of training data sets, correlative algorithms, and networks of circulation remains unmoved, thus reinforcing the idea that the logic of AI is unquestionable.

Queering AI, then, cannot be merely about increasing the diversity of training data (Caliskan 2021), or curating algorithms towards inclusive networking, or putting checks and balances on computational networks in order to keep people safe (Nenad et al. 2021). While all of these are important, they are more post-facto implementations that are more oriented towards reduction of harm and diminishing the violence against Queer bodies that is structurally built into AI platforms and practices (Johnson 2021). A correction of AI's deployment and intention (Hao 2019) is perhaps as futile as trying to de-weaponise a gun, because it reinforces that the way in which AI is being designed and coded is fine, and the only problem is with its implementation and structures of power who wield it (Katyal and Jung 2021).

Instead, queering AI, I propose, is to change some fundamental ways by which we can recalibrate the very computational materiality and digital deployment of AI by changing the parameters through which it weaponises information against queer and other intersectional underserved communities. I have three speculative and material propositions which not only break away from the clean-dirty narrative deadlock but also puts forward demands and challenges of abandoning some of the most problematic practices of AI development and deployment in order to actually serve the needs of queer life and sociality. While these propositions are by no means exhaustive, they do offer an approach of how we might take fundamental building blocks of AI and queer them in order to create AI systems that are in their very nature aligned to queer inclusivity and safety.

Queering the node: The collective as the origin of information

At the heart of digital computation is the construction of nodes in a network. Nodes do not have a linear, comprehensive, origin story where it pre-exists the network and intention of information circulation. The Barabasi-Albert model (Barabasi 2015) of understanding scale-free networks in computational systems proposes a system that works on the ideas of growth and preferential attachment. Both of these ideas work on the concept of a node.

In their model, the node does not have a value or an origin of its own but it accrues value through connecting with other nodes. In their preferential attachment theory, they argue that the more a node is connected, the more likely it is to receive new links. Dubbed in social theory as the Matthew Effect (Rigney 2010): "the rich get richer," this preferential node analysis of contemporary social media networks proposes a radical breakthrough in understanding the impulses of AI deployment.

Most AI work with this preferential attachment theory for their growth, establishing a positive feedback cycle between the node that is already in power and those who link back to it. Which means that AI networks have a clear idea of independent, discrete, and isolated nodes which will be favoured both in terms of amplification of their information as well as in growing their circulation in the favour of smaller, dissident, or less connected nodes. Scale-free AI networks thus insist that the value of information and its spread is proportional to the discrete and individual sources of information. It traces information, through all its social media spread, back only to its "origin sources," thus creating a hierarchy of which node will be preferred in a space of conflict.

This temporal quality, where new nodes are added to a network only one at a time, and reverse engineering collective information to individual nodes, is one of the most definitive ways by which dissident, dissonant, or critical nodes are either removed from the network or devalued in favour of the "origin source" which is seen as the most connected and hence the most authoritative source in the system.

My first proposition for queering AI is to reject this model as the only viable one. While this model is a description of what happens in scale-free networks that are aimed for infinite growth, it doesn't have to be the default model of all AI. In fact, replacing scale with intensity—thus measuring the affective and the emotional experience of being connected—might lead to a new kind of AI which makes space for treating nodes not only as equal but collective.

The idea of making nodes not replaceable but coherent, and continually bleeding into each other, allows for a space of safety, anonymity, and dissidence, without persecution or being dropped out of a network. It resists the kind of experiments of detection which continue to make queerness an individual attribute and uses information shaped by more influential nodes to isolate and target individuals. Instead, it allows for a collective queer spectrum to emerge which will concentrate more on the co-creation of dynamic datasets. These will be valued through their collective origin rather than their connected spread—information becomes more valuable because multiple nodes create it, rather than being valued because multiple nodes circulate it.

Leaning into fragmentation and omission

The algorithmic violence of detection depends upon the premise of intelligibility. Digital intelligibility, which is, as Wendy Chun (2011) points out, a function of storage rather than memory, essentially means that the individual user is mined for data to create composite and discrete images and profiles for pattern recognition and eventual discrimination. The standard response to discriminatory AI has been to give it more information, expand its data sets, and allow for more people to interact with it. However, if the presumption that the AI can and will know everything about us is not shaken, then that AI eventually is going to enter into negotiations of harm (Biernesser et al. 2020) and the cruel algebra of survival, when it comes to decision-making.

Recognising that the biggest role of AI—predictive, detective or otherwise—is in decision-making helps us understand that giving excessive data to AI is not going to resolve the problems. In fact, this was one of the core recommendations from the research team led by Timnit Gebru, where they argued that increasingly we are dealing with large models that defy description and documentation because they are too large to be described—just like a true scaled map of the world would be too large to be accommodated in the world as we know it—and this is leading to potentials for invasive AI manipulations and deployment.

The fundamental problem about "not enough data" in the context of discriminatory AI is that it puts the onus of producing clean, robust, comprehensive data on the individual, at the same time divesting the human user of powers of negotiating and shaping the data. As queer artist Zach Blas suggests in his extraordinary performance that designed the "Fag Facial Recognition Mask" (2014), the biggest resistance to AI is not more data, but obfuscation and production of data that challenges the AI way of seeing things. Blas recommends that data be produced in a relationship of "concealment and imperceptibility" (ibid.), allowing for and naturalising data sets of emptiness, where the emptiness is not seen as a lack but as a resistance to the detection-driven violence it instigates.

The lack of data disrupts the narrative of data reconciliation that produces discrete subjectivities that can be isolated, tracked, managed, and controlled. Within self-learning AI systems, the mechanics of hyperlinking perform causality or synthesis between two disparate objects within the computational networks. When AI algorithms encounter absence or illegible data, they make the decision to either link with a more legible or more viral data set, or set up a process of extreme scrutiny on the subject to mine their data to exhaustion. Naturalising fragmentation and omission, and calling for an AI to stop its decision-making when faced with an empty data set is one way by which the detection and contamination arguments can be stopped.

Moving from fidelity to promiscuity

AI models continue to be persistent in their narrative of contamination by aligning themselves to principles of fidelity, both in aesthetics and in computation. An AI model is presented as the most uncorrupted description of the reality that it is modelling. Based on principles of probability and making transparent the information that it is being shaped on, an AI model will always be nothing more than the data it parses and the network of relationships that is produced by the parsing of that data. An AI system, then, can never lie, because it doesn't produce anything more than an aggregation of legible information and a decision based on the parameters set for resolving a crisis. AI models work and persist, despite their flaws, because their standard of "cleanliness" or dependability is fidelity.

It is undeniable that AI models have near-perfect fidelity to the dataset that it is trained on and works upon. As a self-contained, logical, discrete system, there is very little information or data in that system that can be considered as unmapped, ambiguous, or difficult to understand. Even when the data is flawed, or the information is wrong, the informationality itself is clean and clear. Thus, AI systems might leak data, take wrong decisions, perpetuate violence, amplify discrimination, and make decisions that are flawed in real life, but are still perfect when measured in terms of fidelity. It is this adherence to fidelity, that allows for these systems to punish promiscuity and frame all ambiguity as promiscuous.

In this equation, human realities are already messy, but the technological fear of promiscuity double binds queerness which is also often in contradiction to the heteronormative structures of clearly defined genders, relationships, and sociality. Queerness can sometimes be seen as a celebration of promiscuity—not just a sexual polyamory but a production of kinship, networks, communities, and connections that transcend the traditional structures of marriage, family, and inheritance, which are often violent and exclusionary of queer folk. The insistence that queerness now be constructed on structures of fidelity and be considered as dirty if it does not follow the clearly defined boxes of gender, sexuality, and togetherness (Albert and Delano 2021), emphasises the narrative that Queerness is something that has to be managed by AI systems which, with all their problems, retain high and wireless fidelity to the clean taxonomy of their data sets.

Producing AI which is promiscuous in nature—allowing for variable and forgetful data, neurotic and irrational algorithms, and producing connections which are not descriptions of the present but proposals for the future—makes way for a different kind of AI that supports queerness as a desirable state of being. Instead of modelling queerness for detection and cleaning, we can infiltrate AI systems to make queerness its ontology, and letting go of the control and punish power structures that underlie contemporary AI development (Wareham 2021). The idea of promiscuous AI also makes our bodies joyfully contaminated by desires, aspirations, longing, and belonging, not as a rejection of computational networks but as a deep embrace of it. In this we realise that the new bodies that are being constructed—through regimes of computation and lifestyle, through disciplines of labour and valuation—can be more free and experimental.

This sets up a process where we are not looking at queerness and AI as contradictory, but as reconstitutive, using the intersections of the digital and the human to reconsider how future queer AI can be developed and produced.

Contaminatedly, yours—Or why this is a non-dictionary word that will still be used in this title

It is the ambition of this essay, to present contamination or dirtiness, which is often constructed as a queer attribute that can then be resolved by clean and discrete AI technologies, as an ontology for queering AI, to both exploit and expand upon the processes of co-constitution and co-contamination to think through the nature of evidence, historicity, personhood, and embodiment. The attempt is to overturn the idea of the digital as clean and the queer body as contaminated or something that needs to be detected and sanitised.

In evaluating the detective, predictive models of AI and their operations on queerness, I show that our responses cannot merely be correction and improvement, but a recognition that queerness is needed to be dirty for AI technologies to model and present themselves as clean and dependable. Through this chapter, I have argued that we need to see contamination of queer, by queer, through queerness, as deployed in the weaponised AI practices, as a pre-requisite for the technology itself to sustain its hold and power despite the multiple flaws in its own unfolding.

I offer that a part of our queering of AI is not just to give queer data and algorithms to existing AI structures, which will only use this information to create a larger expanse of discriminatory and exploitative models. We move beyond the "better data" rhetoric and start examining the ways in which AI logics and mechanics can be deployed for human needs, offering intensity rather than scale, as the parameter, thus overturning the idea of AI as the measure of queerness, and instead establishing queerness as the lens through which AI can be developed. Instead, our attempts at queering AI have to be an ontological reworking of some of its computational and discursive practices and definitions, intentions and ambitions, and in the process, create the challenges and opportunities of making queerness as a source for joyful expansion rather than shrinking detection. In this, we depathologise queerness from AI modelling systems, and make way for new celebrations of collective, fragmented, and promiscuous AI systems that can harness the potential of queerness to create kinships and collectivities that contaminate the gentrified digital futures with joyful possibility.

Note

1 The pre-print version was published online in 2017 at https://psyarxiv.com/hv28a/. Most of the responses are to that paper and hence that is the cited date. The article was published with minimal changes in the *Journal of Personality and Social Psychology* in 2018. The reference notes that subsequent responses have addressed that.

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