Not Content

How the algorithmic telos cultivates radical political outcomes by its recommendation of media

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January 2024

Abstract

This paper investigates a gap in prior research into algorithmic recommendation. Namely, the precise interactive mechanism between the corporate end-goal of user retention, and the outcomes that eventuate from it, including radicalisation and violence. I show that both premises have been established by prior research and explore how the formal traits of media on algorithmically curated platforms that maximise user retention also lead to ideological extremism.

I achieve this through analysing patterns in recommendation using an experimentally generated dataset of algorithmically autoplayed media as proxy. I track the suggested videos of YouTube accounts with a range of simple existing media habits to account for the impact of pre-existing political preferences that have been the focus of much of the existing literature. Therein, I find that more universal factors drive recommendation.

Results indicate that while there are clear correlations in the formal factors, the actual content of recommended media develops erratically and with little evidence of a linear progression towards politically radical outcomes. Instead, recommendations follow patterns of type, with a continuity of genre, and user demographics especially, with little coherence in the actual topic. Promoted media share a number of apparently algorithmically privileged formal factors — notably runtime, sensationalism, misinformation and niche — which I reason are also formal factors shared disproportionately by radical reactionary content.

My research thus demonstrates the formal factors discussed in my thesis that encourage increased user retention above all else are also those associated with extreme content. Industry attempts to address platforms' radicalisation pathways from algorithmically-driven content with post hoc content moderation is inadequate. In combination with prior literature, my findings suggest that social media recommendation motivated by this telos of retention maximisation for profit pushes users toward media with the formal factors and impact on the user that radical content has.

Keywords

Algorithm recommendation, online radicalisation, surveillance capitalism, media analysis, YouTube.

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Declaration:

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for a degree or other qualification at this University or elsewhere. All sources are acknowledged as references.

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Introduction

1.1 Background

Algorithmically-driven social media platforms such as YouTube are biased towards the perverse incentive of user retention, "convincing the user to watch an additional video after the end of the first video has finished," above all else.¹ Bias is the preference of one outcome over another, which is exactly the function of recommendation. But unlike the complex combination of human motivations for recommendation, balanced against one another, machine learning algorithms are driven by the pursuit of the pre-set end goal Bryant describes. In this thesis I will refer to this pre-set end goal of user retention as an algorithmic telos, from the Greek, meaning an ultimate aim, or eventual, inevitable destination.

Shoshana Zuboff's influential reframing of digital culture in *The Age of Surveillance Capitalism* describes this telos as an "extraction imperative" for user attention and thereby data to be "procured at an ever-expanding scale".² Algorithm engineers talk of 'maximising retention', but at the highest and lowest levels alike, this telos is a simple profit motive. "The goal of the algorithm is to drive users to use the service as much as possible, [...] generating revenue for the website."³ But this pursuit of profit in itself fails to explain a pattern of dangerous outcomes observed on these platforms.

Scholars have shown that the outcomes of algorithmic recommendation make digital space hostile, and manifest violence the real world. For instance, Michael Edison Hayden of the Southern Poverty Law Centre links together the mass shootings in El Paso, Christchurch, and Poway, in which the shooters "published manifestos to 8chan" concerning political conspiracies with a "large audience on YouTube".⁴ Regarding extremist violence, social media is involved both in its execution — the Christchurch shooting was streamed live on Facebook — and as explanation. Eli Pariser suggests the user filtering that drives social media recommendations drives users away from the centre ground, ⁵ and regarding YouTube specifically, Ribeiro et al found, "users consistently migrate from milder to more extreme content."⁶ But Luke Munn contests that this radicalisation via recommendations occurs symmetrically across a political spectrum, arguing that "fillter bubbles not only reinforce existing views, but amplify them and generate new ones".⁷ Similarly, Lauren Bryant's paper, 'The YouTube Algorithm and the Alt-Right Filter Bubble' finds both that algorithmic recommendation online "has a strong bias towards right-leaning politics," and that "many of the mass shooting attacks worldwide have been traced back to a small, thriving online community."⁸

Moreover, Kaiser and Rauchfleisch's 2018 study, shows that casual perusers of right-of-centre political media are, in their words, "only one or two clicks away" from extremist content.⁹ They

¹ Bryant, Lauren (2020) 'The YouTube Algorithm and the Alt-Right Filter Bubble' *Open Information Science*, vol.4, no.1, p.86.

² Zuboff, Shoshana (2018) *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. Profile Books. Ch.3, pt.VII.

³ Bryant (2020) p.87-89.

⁴ Hayden, Michael Edison (2019) 'New Zealand Terrorist Manifesto Influenced by Far-Right Online Ecosystem, Hatewatch Finds', *Southern Poverty Law Centre*, 15 March,

https://www.splcenter.org/hatewatch/2019/03/15/new-zealand-terrorist-manifesto-influenced-far-right-online-ecosystem-hatewatch-finds.

⁵ Pariser, Eli (2011) *The Filter Bubble: What the Internet is Hiding from You*. New York: Penguin Press

⁶ Ribeiro, M. H., Ottoni, R., West, R., Almeida, V. A., & Meira Jr, W. (2020, January). 'Auditing radicalization pathways on YouTube.' In *Proceedings of the 2020 conference on fairness, accountability, and transparency* (p.131).

⁷ Munn, Luke (2019) 'Algorithmic Hate: Brenton Tarrant and the Dark Social Web', *Institute of Network Cultures*.

⁸ Bryant (2020) p.85.

⁹ Kaiser and Rauchfleisch (2018).

ascribe this proximity to an algorithmic generalisation between centre-right and far-right content, and the "ever-more-radical recommendations that YouTube throws your way."¹⁰ The outcomes of recommendation algorithms' filter bubble' process snowballs towards reactionary views and content, a far-right politics in "opposition to feminism, social justice, or left-wing politics."¹¹

And this process of radicalisation online interlocks a number of social media platforms. The Qanon conspiracy theory, an umbrella explanation of every typo of the Trump presidency in the form of an anonymous, interactive, ARG-style game of riddles with a real life body count,¹² "emerged from the primordial swamp of the internet on the message board 4chan."¹³ And as Luke Munn shoes, social media platforms "allow ideas and events to move beyond an individual's immediate circle and spread quickly," suggestion there is no doubt, for instance, that "Facebook Live and Twitter helped [the Christchurch shooter's] videos and writings to spread."¹⁴ Researchers have described that far-right groups "organized on Facebook,"¹⁵ and used YouTube as "an informational cornerstone."¹⁶ In *Upvoting Extremism*, researchers of the radicalisation on Reddit implicate the platform "voting algorithm in facilitating 'othering' discourse and, by extension, collective identity formation" in the internet's most radical spaces.¹⁷ Ordinary public social media and these radical spaces "appear to be merging, feeding off each other to form a cohesive online environment."¹⁸

Attempts to halt this process with moderation have failed. YouTube claim that changes to the algorithm to "reduce recommendations of borderline content and harmful misinformation" resulted in a "70% average drop in watch time" for certain types of user.¹⁹ However, their blog posts predate Bryant as well as other research this thesis will later explore (see section 2.4), demonstrating that this phenomenon of radicalisation has persisted despite YouTube's effort. Moreover, that this right-biased radicalisation occurs across platforms²⁰ suggests that instead of being a by-product of a specific company's recommendation algorithm, it is the universal fundamentals of recommendation which result in radical outcomes, as my thesis will argue.

1.2 Research question, approach, and aims

The indicated connection between the overriding logic of social media and the extreme real-world impact of the media environment it creates leave an unanswered question of process: *how does the algorithmic telos cultivate radical political outcomes by its recommendation of media?*

As described in the *Post-Human Glossary*, "algorithm studies," have explored these "algorithmically compelled (pre-)dictable futures," from Ignacio Siles to Lauren Bryant, showing how the output of

- YouTube' Data and Society, https://datasociety.net/library/alternative-influence/ accessed 06/06/2023.
- ¹² Beckett, Lois (2020) 'QAnon: a timeline of violence linked to the conspiracy theory,' *The Guardian*, https://www.theguardian.com/us-news/2020/oct/15/qanon-violence-crimes-timeline.

¹⁰ Kaiser and Rauchfleisch (2018).

¹¹ Lewis, Rebecca (2018) 'Alternative influence: Broadcasting the reactionary right on

¹³ Wong, Julia Carrie (2020) 'QAnon explained: the antisemitic conspiracy theory gaining traction around the world,' *The Guardian*, https://www.theguardian.com/us-news/2020/aug/25/qanon-conspiracy-theory-explained-trump-what-is.

¹⁴ Munn (2019).

¹⁵ Wong (2020).

¹⁶ Kaiser and Rauchfleisch (2018).

¹⁷ Gaudette, T., Scrivens, R., Davies, G., & Frank, R. (2020) 'Upvoting extremism: Collective identity formation and the extreme right on Reddit', *New Media and Society*, vol. 23. no. 12, Dec, 3491–3508.

¹⁸ Munn (2019).

¹⁹ The YouTube Team (2019) 'The Four Rs of Responsibility' *The YouTube Blog*, https://blog.youtube/inside-youtube/the-four-rs-of-responsibility-remove/.

²⁰ Merril, Jeremy B. and Will Oremus (2021) 'Five points for anger, one for a 'like': How Facebook's formula fostered rage and misinformation', *The Washington Post*, 26 October,

https://www.washingtonpost.com/technology/2021/10/26/facebook-angry-emoji-algorithm/.

recommendation systems leads to, among other outcomes, scocio-political radicalisation.²¹ The field of algorithm studies has, too, defined the broader social, economic, and political scope toward the whole industry, as "a critique of algorithmic capitalism [and] its mode of production," according to Zuboff. But it is the under-analysed process from which the latter mode of production produces the former algorithmically compelled futures which is the focus of this thesis. In bridging this blackboxed gap in the literature, this thesis thus aims to demonstrate a direct and indelible causal link between the profit motive telos and the ultimate outcomes of radicalisation isolation and violence.

This thesis will address its research topic by first examining existing literature, with a focus specifically on these two areas of research. First, the study of the economics of social media, and of how the pursuit of profit is parent to the principles of media recommendation, which serve to guide users to specific media more nefariously than through simple reflection of existing preferences. Second, the actual outcomes of recommendation, demonstrating a pipeline of radical content and its impact on users, with a focus on contemporary research.

I then supplement the literature review with a set of simulations of the user experience on YouTube via 3 specifically generated cases consisting of long threads of recommended videos. I code each proxy user with simulated existing preferences, and each watches a run of auto-played videos, guided by the recommendation system, and I find the patterns in recommendation as they emerge. The simulated preferences include one right-leaning user, one left-leaning user, and one user with no existing media habits, so as to generate examples with variety representative of actual users.

I then track the nature of the content being recommended, its topic, tone, and political essence, as well as the formal qualities, such as runtime and viewer numbers. Using the generated case studies that are recommendation pathways through the YouTube media landscape, I analyse both specific media and trends in media recommendation to describe the observable outcome tendencies of the black-boxed algorithmic process. These findings link together the established telos of user retention stemming from the platform's profit-motive with the documented result of radicalising patterns in recommendation.

By analysing tendencies in recommendation through this generated dataset, I show a pattern of preferences and how those preferences are born from that ultimate profit-seeking telos described by prior research. I then identify a series of 'mechanisms', meaning types of interactions between a user's behaviour and algorithmic practice. These mechanisms demonstrate how the fundamental aims of the algorithmic systems result in the outcome of an apparent bias toward radical content described by that second body of existing literature. I demonstrate therein that the cultivation of radical political outcomes is the natural end-result of a system built for profit first, rather than an aberration.

Ultimately, I indicate the need for fundamental change in the priorities of social media platforms and the use of recommendation algorithms if they are to effective combat the prevalence of these radicalisation pathways. Until the fundamental aims of these systems are reimagined, the recommendation of isolating, extreme content will persist and the resultant real-world impact will continue to be felt.

²¹ Ng, Jenna and David Theo Goldberg, 'Algorithmic Studies,' (2018) in *Posthuman Glossary*, ed. Rosi Braidotti & Maria Hlavajova.

Literature Review

2.1 The epistemological problem of algorithm studies

The field of algorithm studies already has a wealth of research, practical and theoretical as a convergence point of media, sociological, anthropological, and economic studies.²² Theorists and practitioners from a range of backgrounds have contributed to the body of research which necessarily involves the collection of ideas from different fields because of the sheer scope of the topic at hand. Increasingly, the recommendations of algorithms, whether to content consumers or potential employers or banks or courts don't just touch every aspect of modern social life, but influence it in both subtle and indiscrete ways, leaving "no area of human experience untouched".²³

The distinguishing feature of our everyday interaction with social media recommendation algorithms is that we do not actually interact with the algorithms directly. Instead, we interact with the text of the content that it recommends (be it documentary film, music, podcast, live sports, news, home videos, etc.), and the ludo-logical or "gamified"²⁴ meta-text of 'likes' and 'dislikes' and "don't recommend videos like this" buttons. Research such as Siles's 'Learning to like TikTok... and not: Algorithmic Awareness as process' has established that "use of platforms leads to more awareness of algorithms,"²⁵ with "many more" experiment subjects using the term "algorithm" to describe their relationship with TikTok content after even a short period of use.²⁶ But as they note, this "umbrella term" for "specific computational procedures to recommend content"²⁷ is itself a vagueness; even as users develop a push-pull relationship, or "domestication" of recommendation systems.²⁸

Beth Singler further discusses the indirectness of the user's relationship to 'artificially intelligent' recommendation systems, identifying the proliferation of the idiom "blessed by the algorithm" to express how users are "subject to the whim of" recommendation systems.²⁹ She describes how the power imbalances of the user/algorithm relationship "map onto [...] familiar theistic interpretations of how to gain a god's/or gods' favour," but this language also reflects the obscurity of gods, to which you have to pray only because you have no direct access.³⁰ Similarly, Siles et al observed the independent linguistic emergence of the term 'The Algorithm' "often in the singular" preceded by the definitive article, which reinforces this notion of deification as an independently intuitive reaction to the dynamics of recommendation algorithms in digital culture.³¹ In one direction, algorithms "shape and direct the very way we think,"³² and in the other, users have only a limited conceptualisation of what 'The Algorithm' even is.

In recognition of this contradiction central to algorithm studies, my approach to literature and methodology is informed by Tania Bucher's article for *Innovative Methods in Media and Communications Research*, 'Neither Black Nor Box: Ways of knowing recommendation algorithms'

²² Gillespie, T. and Seaver, N. (2016) 'Critical Algorithm Studies: a Reading List', Social Media Collective.

²³ Seyfert, Robert and Jonathan Roberge (2016) *Algorithmic Cultures: Essays on Meaning, Performance and New Technologies,* Routledge Advances in Sociology.

²⁴ Van Rijmenam, Mark (2017) 'Why Gamification is the Friendly Scout of Big Data', Datafloq,

https://datafloq.com/read/gamification-is-the-friendly-scout-of-big-data/.

²⁵ Siles, I., Valerio-Alfaro, L., & Meléndez-Moran, A. (2022). 'Learning to like TikTok... and not: Algorithm awareness as process.' *New Media & Society*, 0(0) p.14.

²⁶ Siles et al (2022) p.8.

²⁷ Siles et al (2022) p.8.

²⁸ Simpson, E., Hamann, A., Semaan, B. (2022) 'How to tame "your" algorithm: LGBTQ+ users' domestication of TikTok'. *Proceedings of the ACM on Human-Computer Interaction* 6(GROUP): 1–27.

²⁹ Singler, Beth (2020) "Blessed by the algorithm": Theistic conceptions of artificial intelligence in online discourse.' *AI & Soc* 35, p.949.

³⁰ Singler (2020) p.952.

³¹ Siles et al (2022) p.8.

³² Berry, David M. (2023) 'The Explainability Turn', *Digital Humanities* Quarterly, Volume 17 Number 2.

and the chapter in *If... Then: Algorithmic power and politics* on the same theme³³. The two works outline a prospective method for researchers to broach the issue of the closed systems and closely kept secrets of recommendation algorithms, known in the field as the "black box" problem.³⁴ Bucher's theory will be the foundation of my methodological approach, and will inform the selection of literature, too, in order to face the "serious conceptual, epistemological, and methodological challenges" of knowing algorithms.³⁵

Based on her own meta-analysis of past study, Bucher's three headline recommendations for investigating the inner-working of the recommendation machine are as follows:

- a. Do not fear the black box.
- b. Do not expect the answer to any algorithmic questions about to be inside the black box.
- c. Consider the 'boxing' of the box.

The summation here is that, while the box itself might be an epistemological black hole, a small corner of our increasingly digitalised society out of sight of the human public, it can be understood, by taking a step back from the box itself: Though there is no way of seeing into a black box, one can observe its inputs and outputs and understand the black box's contents, at least to a degree, by its place in a wider context.

And, by the same logic, a black-boxed recommendation system can itself be better understood with a broader sociological and especially economic perspective. Bucher describes the meta black box: just as the algorithmic processes of recommendation are closed away and hidden, the processes of design and independent evolution used to grow this decision-making machine are closed away as well. As such, the very development of the black box is itself black-boxed. So my deployment of the "black box" metaphor refers dually to the micro-scale logic of individual interactions and user recommendations as to the macro-scale logic of the widest algorithmic patterns and trends. Therefore, this thesis's focus on radicalisation online isn't only about identifying an area of danger and concern, but practically minded, too, as "algorithms particularly reveal themselves in moments of disruption".³⁶

Keeping up with a system defined by its speed of growth and totality of adaptation means that even with a focus on texts from the last few years, literature can become outdated quickly. Regarding questions of radicalisation, especially, recommendation platforms are continuously updating their systems and re-stating that the problems are being solved. Regarding borderline extremist content, that is content with notably strong politics without breaching specific rules, YouTube makes lofty claims that, just in 2019, "30 different changes" summed to a "70% average drop in watch time" of radical content from passing viewers.³⁷ Fast-moving developments like these threaten to outpace research, claiming to have appropriately met the criticism of papers published as recently as 2020.

As such I have focussed on empirical studies from the past few years, namely 2019-2023. In reaction to the evasively ephemeral nature of any and every specific instance of algorithmically-driven recommendation, as well as the broader issues of black-boxing outlined, this research takes a wider focus on generalised logics. Hence, much of the relevant literature is more theory-driven, with direct evidential reinforcement where and when possible. As Bucher argues in *If... Then*, "algorithms are

³³ Bucher, Tania (2018) *If... Then: Algorithmic Power and Politics*, Oxford University Press, ch.3 p.41-65.

³⁴ Bucher, Tania (2016) 'Neither Black Nor Box: Ways of Knowing Algorithms.' In: Kubitschko, S., Kaun, A. (eds) Innovative Methods in Media and Communication Research. Palgrave Macmillan, Cham.

³⁵ Bucher (2016), p.82.

³⁶ Bucher (2016) p.91.

³⁷ YouTube (2019) 'The Four Rs of Responsibility, Part 2: Raising authoritative content and reducing borderline content and harmful misinformation,' *YouTube Official Blog*, https://blog.youtube/inside-youtube/the-four-rs-of-responsibility-raise-and-reduce/.

socio-material practices, not merely a set of coded instructions"³⁸ which "reflect the values and cultural assumptions of the people who write them."³⁹

Consequently, in order to understand these media recommendation algorithms, my approach involves discussion of that broader culture of values and assumptions, as in the following sub-sections. The "institutional choices that lie behind these cold mechanisms,"⁴⁰ like the algorithms themselves, follow a simple telos in their pursuit of profit.

2.2 The economics of online space

Former Google Design Ethicist, Tristan Harris, cites a "classic saying" in the 2020 documentary *The Social Dilemma*: 'If you're not paying for the product, then you are the product'. Zuboff offers a slight adjustment to what she sees as a misjudgement:

You are not the product; you are the abandoned carcass. The "product" derives from the surplus that is ripped from your life.⁴¹

Her work here, a Marxist reinterpretation of the economical logic of digital culture, helpfully grounds unprecedented contemporary developments in a history of established theory. The juxtaposition of material economic analysis with the often obscured logic of data interaction online draws a direct connection from a tangible profit incentive to tangible outcomes for users. In those terms, then, she argues that social media is neither a product nor a service, but an apparatus for resource extraction.

But to conflate this new economic relationship with digital culture directly would be a mistake, because while heightened by algorithmic curation on social media, the use of media as a method of value extraction from consumers has much earlier roots. Harris's turn of phrase originates, so far as I can find, with an earlier generation of media curation, in the short film *Television Delivers People* (1973). As its director, Richard Serra argues: "It is the consumer who is consumed".⁴²

Also concerned with the developing economic logic of television and digital content, John Dimmick provides a clarifying conceptual framework for understanding developments in media as the outcome of selection processes similar to those in evolutionary theory.⁴³ He applies principles originally observed in speciation and species' specialisation to media ecosystems on the basis that the same funamental logic applies to both: survival of the fittest. Each media iteration is created with certain traits which are, if the work succeeds by a given metric (e.g. viewership, profit, critical celebration), passed down to newly created media in the same system. This work draws specifically on "the theory of the niche," to describe how, like animal ancestry, media adapt to increasingly specific gaps in its environment. This framework is especially applicable to generations of algorithmically recommended media, such as those in this thesis's case study because of the sheer speed and number of 'generations' involved in personalisation. Each algorithmic recommendation provides the system more information, which informs the next recommendation, which provides more information, proceeding in this evolutionary pattern, but exaggerated by the rate of change and the fact that each user's recommendations are undergoing a parallel process of the same kind.

Exemplifying this theory of the niche, modern digital media curators use the mutability of online space to modify and manipulate the experience extensively to each user, down to how streaming

³⁸ Bucher (2018) p.152.

³⁹ Bucher (2018) p.90.

⁴⁰ Guillespie, Tarleton (2014) Ch. 9: The Relevance of Algorithms, in *Media Technologies: Essays on Communication, Materiality, and Society*, Cambridge, Massachusetts: MIT Press Scholarship Online. p.169.

⁴¹ Zuboff (2019) ch.13, pt.1, p.344.

⁴² Serra, Richard (1979) interviewed by Annette Michelson in "The Films of Richard Serra: An Interview," *Richard Serra: Interviews, Etc.* 1970-1980, Archer Fields Pr. 2nd ed.

⁴³ Dimmick (2003) *Media Competition and Coexistence: The Theory of the Niche*, 1st Ed. Routledge.

platforms "construct [their] homepage" to "guide people towards the content."⁴⁴ But surveillance capitalism in the 21st Century was built on the existing systems, out of the existing relationships, of the modes of media capitalism in the 20th, itself simply extrapolating out from its origins in the 19th. "The internet of things" makes for a modern Panopticon, but it is worth remembering that the Panopticon itself originated with Jeremy Bentham's brother, Samuel's "circular two-story factory" in the early industrial workplace, in direct dynamics of labour and capital.⁴⁵

However, generalising the economic logic of data-harvest capitalism like this risks becoming reductive because of the different logics of different platforms. For example, Google provides so many services across so many different branches of business, and even YouTube alone comprises multitude functions from chatrooms to casual video hosting to paid film and TV streaming. Facebook is a messaging platform, an entertainment recommendation system, a community forum, a marketplace, etc. But from Zuboff's top-down perspective, these plethora of different ventures "are actually all the same activity guided by the same aim: behavioral surplus capture".⁴⁶ Her terminology derives from the economic theory of surplus value, describing the portion of an industrial product "left over to sell and turn into revenue" after accounting for labour.⁴⁷ In the specific case of data corporations, a behavioural surplus is that "behavioral data available for uses beyond service improvement" which is "fed into advanced manufacturing processes [...] and fabricated into prediction products."⁴⁸ These products are "predictions of user behavior,"⁴⁹ and can be sold as a service to advertisers and "used to enhance and tailor [...] marketing messages to a very high degree,"⁵⁰ or even leveraged by the company for its own purposes.

These 'advanced manufacturing processes' are another black box, vast collaborative arrays of machine learning and human engineering that turn personal data into prediction. Recommendation is only the user-facing purpose of behavioural data capture, for the improvement of products and services. Certainly some data harvested is used for the purpose of service improvement and personalisation, but all of this data collected is also stored and processed into predictive reserves of information capital. Unlike physical, industrial produce, the information capital collected by data services can both be used for the legitimate improvement of user personalisation, and repurposed into prediction products, which makes 'behavioural surplus' an analogy of limited usefulness.

Describing user-facing personalisation as a legitimate use of behavioural surveillance, separate to the surplus used to manipulative ends, is to disregard the extent to which digital services themselves deploy behavioural prediction in their recommendation of content. The personalisation of the service is itself exists to guide user behaviour, just as much as that sold to advertisers, and as such, it isn't possible to draw a distinction around 'surplus' surveillance data. Engineering Director Justin Basilico answers the question "why do we personalize?" with the explanation that Netflix "maximise [their] members' satisfaction and [...] that also maximises the chance that they're going to stay a member and pay their membership".⁵¹ Personalisation for user satisfaction and behavioural influence for profit are not separate functions of recommender systems, but one and the same.

In the case of Google's YouTube, Zuboff quotes a software director that "the real aim is ubiquitous intervention, action, and control,"⁵² which is what social media recommendation and personalisation is. Media recommendation online operates in this mode of surveillance which then leverages

⁴⁴ Basilico, Justin (2019) 'Recent Trends in Personalization: A Netflix Perspective', SlidesLive, hosted by International Conference on Machine Learning (ICML), 15 June,

https://slideslive.com/38917692/recent-trends-in-personalization-a-netflix-perspective, 1:40.

⁴⁵ Roth, Michael (2006) *Prisons and prison systems: a global encyclopedia*, Bloomsbury Academic, p.33.

⁴⁶ Zuboff (2019) ch.5, pt.1, p.118.

⁴⁷ Zuboff (2019) ch.3, pt.3, p.63.

⁴⁸ Zuboff (2019) ch.3, pt.3, p.63, and ch.1, pt.3, p.14.

⁴⁹ Zuboff (2019) ch.11, pt.3, p.310.

⁵⁰ *Criteo* (2015) "Ovum Report: The Future of E-Commerce—the Road to 2026," cited in Zuboff (2019) ch.8, pt.2, p.226.

⁵¹ Basilico (2019).

⁵² Zuboff (2019) ch.10, pt.1, p.268.

information about a user toward specific outcomes that are more profitable for the corporation running the platform. And *Television Delivers People* explains this relationship between audience and media curators succinctly: "You are the product of TV." The actual service that content recommendation platforms deal in is the future decisions of their users.

2.3 Human agency and the stories of our lives

While specific data on YouTube's mechanisms against borderline content and misinformation isn't public, their PR pages assert that "recommendations systems help limit the spread," which presents a semantic problem that is revealing in and of itself: The YouTube recommendation system helps limit the amount of ugly content spread by the YouTube recommendation system itself.⁵³ Describing it as a success of their platform, YouTube assert the recommendation algorithm is virtuous for its role in reducing the proliferation of dangerous content, but that proliferation is also the outcome of the recommendation algorithm. The company celebrates that fewer users are being actively promoted harmful content than previously, but it is YouTube themselves that were and still are promoting that content in the first place and at all. Either YouTube has sufficient control over the patterns of recommendation by its algorithm and it allows dangerous content, or it does not have sufficient control. The terminology from Spotify's personalisation team, "algotorial" is a fitting portmanteau metonym for this contradiction inherent to recommendation; the first of the component words, 'algorithm', describes a simple goal-oriented system with no capability for real judgement, and the second, 'editorial', ordains ultimate authority over the media and media system in question, and yet the two are combined nonetheless.⁵⁴

This paradox of purpose cuts to the heart of the issue.

Zuboff's Marxist analysis frames this paradox as class tension, wherein data corporations own surveillance software and predictive algorithms which are fuelled by those who do not own the capital, though in this case, "instead of labor, surveillance capitalism feeds on every aspect of every human's experience." However, a broader anthropological perspective describes the conflict as something more existential; as a question of agency more broadly. "The danger that the computer poses is to human autonomy," Paul Schwartz wrote at the beginnings of digital culture in 1989. "The more that is known about a person, the easier it is to control him."⁵⁵ In simplest terms, lending credence to the Marxist perspective, agency is a question of power. A question of whether one has the power to follow one's intentions through to action and actualising change in the world.

However, the role of "free will" in any of our actions, let alone on the scale of mankind more widely, is quite possibly the single biggest open question in the history of philosophy. To discuss agency in a few broad strokes: In David Graeber's posthumous overview of the human experience, *The Dawn of Everything*, he and David Wengrow approach the definition of *agency* from an anthropological, historiographic perspective, finding 'free will' a fuzzy and indefinable term. They note that retrospectively, the role of human agency is almost entirely eliminated from accounts of events because "as soon as those events do happen, we find it hard to see them as anything but inevitable." ⁵⁶ Rather, they assert 'human agency' at every turn in the story of humanity, deconstructing the modern de-centring of human decision-making from historical narratives. Graeber and Wengrow evidence the

⁵⁴ Stål, Oscar (2021) 'Adding that extra YOU to your discovery', Spotify Newsroom, 13 October,

⁵³ YouTube 'Does YouTube contribute to radicalisation?'

https://www.youtube.com/intl/ALL_uk/howyoutubeworks/our-commitments/curbing-extremist-content/ #curbing-borderline-content.

https://newsroom.spotify.com/2021-10-13/adding-that-extra-you-to-your-discovery-oskar-stal-spotify-vice-president-of-personalization-explains-how-it-works/.

⁵⁵ Schwartz, Paul (1989) 'The Computer in German and American Constitutional Law: Towards an American Right of Informational Self-Determination,' *American Journal of Comparative Law* iss.37 p.676.

⁵⁶ Graeber, Wengrow (2021) *The Dawn of Everything: A New History of Humanity*, Farrar, Straus and Giroux p.206.

role of human agency in the agricultural revolution by the slow adoption of 'civilised' agricultural society, as well as the fact that many societies turned down the opportunity when it arose.

Through a similar lens to Graeber and Wengrow's framing that societal change as a product of human agency and broad consent of a population has historically been a slow and deliberate process, Zuboff describes the inverse process as a "dispossession cycle".⁵⁷ This term refers to the repeating process by which privacy and autonomy have been eroded, and she underlines the extreme speed at which it occurs, spearheaded by technology companies who stepped over ordinary legal barriers to get their new financial systems up and running. Breaking this cycle into individual steps, Zuboff calls the process by which surveillance capitalism increasingly inserts itself into ordinary life without consent "incursion" and gives, as an example, Street View, with which Google "took what it wanted, waiting for resistance to run its course."⁵⁸ Following this is a process of "habituation" in which the invasion of privacy provides just enough "access to new qualities of information, new conveniences" that the questionable legality of the original incursion can be ignored.⁵⁹

On the scale of the agency of the individual user, Netflix's Engineering Director claims recommendations are responsible for "over 80% of what people watch" on the platform on the basis that any time users access content through their homepage, they are accessing content through a medium of recommendation.⁶⁰ It is, of course, impossible to actually quantify a percentage of user decisions determined by algorithmic recommendation, even were one actually privy to the precise clockwork of the black box, which even its engineers are not. The question of where exactly guidance, influence, and recommendation topple into manipulation and control is philosophical in nature, but as with the 'black box' this thesis investigates the unknown in-between by drawing out the aims of recommendation systems and comparing that with the literature exploring online algorithm's dangerous outcomes.

Another dominant indication of the diminished role of human agency in our digital culture is the 2008 study by Aleecia M. McDonald and Lorrie Faith Cranor, which totted up the hours every year every American internet user would have to spend reading the terms and conditions of "each site they visit just once a year".⁶¹ To fulfil the 'informed' requirement of 'informed consent' users would have to read for hundreds of hours a year, equivalent in their final workings to "an average of 40 minutes a day,"⁶² with a national cost of 50 billion working hours and 700 billion dollars. This research demonstrates that, taking a broader view on digital culture societally, it is not plausible for the average user's relationship with the various platforms that make up the modern 'online' to be based on fully informed consent.

Again, Zuboff draws comparisons between industrial capitalism's conventionally coercive contracts and digital culture's similar "obvious lack of meaningful consent,"⁶³ suggesting a continuity of imbalanced power relations between capital and its subjects, while also suggesting an even further "degradation" of contractees' ability to say no. She cites legal scholar Margarette Radin's terminology of the "private eminent domain," — the state's power to seize property reoriented, via digital contracts marking dubious consent, into a tool of private industry — to describe the system of surveillance on the internet as "a unilateral seizure of rights without consent". In fact, as McDonald and Cranor show, the only sense in which internet users do consent via pop-up internet contracts *is* the strictly legal one.

⁵⁷ Zuboff (2019) ch.5, pt.3, p.127.

⁵⁸ Zuboff (2019) ch.5, pt.3, p.130.

⁵⁹ Zuboff (2019) ch.5, pt.3, p.128.

⁶⁰ Basilico, Justin (2019) Recent Trends in Personalization: A Netflix Perspective', SlidesLive, hosted by International Conference on Machine Learning (ICML), 15 June, https://slideslive.com/38917692/recent-trends-in-personalization-a-netflix-perspective.

⁶¹ McDonald, A. and Cranor, L. (2008) 'The Cost of Reading Privacy Policies', *A Journal of Law and Policy for the Information Society*, vol. 4, no. 3, p.544.

⁶² McDonald, Cranor (2008) p.561.

⁶³ Zuboff (2019) ch.2, pt.5, p.44.

2.4 The political outcomes of recommendation.

The literature in this section demonstrates political outcomes out of the recommendations of algorithm-driven systems. These political outcomes are not all alike: Sophie Bishop's 'Anxiety, panic and self-optimization' finds "polarized gendered" recommendations on YouTube;⁶⁴ Lauren Bryant finds that Google promotes "alt-right" content through a process of "filter bubbles";⁶⁵ Lauren Edelson et al's 2021 study finds that Facebook's systems of engagement promote misinformation so strongly that "posts from misinformation news providers receive consistently higher median engagement than non-misinformation."⁶⁶ These patterns of recommendation are observed on different platforms, even those owned by different parent corporations, and they demonstrate media biases of different kinds, seemingly on different grounds, be they gender, political polarity, factual accuracy, or any other. And while, to an extent, the different interactive logics of different platforms encourage different outcomes, I argue in this thesis that these biases indicate a shared cause in one fundamental telos, shared by all recommendation algorithms despite their parentage or platform particulars.

In the literature around recommendation algorithms' political outcomes I identify two orthogonal themes, which intersect but are themselves independent from one another: an 'extremification bias', and the selection of specific politics. By 'extremification bias' I refer to the observed tendency of recommendations to guide users towards extremes, which includes Bishop's observations of the polarisation of identity markers on YouTube resulting in "stratification by class and gender".⁶⁷ This is not directly an observation of political extremification in a partisan sense, as seen in other research, but a more inherent extremification of all content on the platform, which is no less political in its outcomes. The extremification bias is in no way limited to strictly partisan binaries or the reductive axis of a national political spectrum. Bishop finds this logic replicated along the axis of gender expression.⁶⁸ Measuring by engagement, the platform prefers "highly gendered" media and "the polarization of identity markers" more generally, summing to a "hegemonic, feminized" ecosystem.

On the other hand, the selection of specific politics does demonstrate an algorithm's specific partisan political preferences by biasing toward a particular political pole, rather than simply radicalising equally in all directions. Kaiser and Rauchfleisch's research describes a "YouTube-created right-wing filter bubble," specifically directing users in a specific partisan direction.⁶⁹ The researchers start from politically central content and map patterns in recommendation, finding that while "the far-left on YouTube is not very visible when you follow the platform's recommendation algorithms," when it comes to mapping the links between more centre and far-right content "YouTube's algorithm [...] connects them visibly."⁷⁰ Drawing this distinction between modes of recommendation bias that do or do not directly privilege right-wing political content is useful for discerning how such political outcomes result from a theoretically politically neutral telos of retention maximisation. There is a clear causal link from an algorithm aiming to retain its audience to the promotion of increasingly

⁶⁴ Bishop, Sophie (2018) 'Anxiety, panic and self-optimization: Inequalities and the YouTube algorithm.' *Convergence: The International Journal of Research into New Media Technologies*. Vol 24, Issue 1, 10 January. p.81.

⁶⁵ Bryant, Lauren (2020) 'The YouTube Algorithm and the Alt-Right Filter Bubble' *Open Information Science*, Vol.4, Issue.1, p.85.

 ⁶⁶ Edelson, Laura, et al (2021) 'Understanding Engagement with U.S. (Mis)Information News
 Sources on Facebook,' *Proceedings of the 21st ACM internet measurement conference*,p.444
 ⁶⁷ Bishop (2018) p.80.

⁶⁸ Bishop, Sophie (2018) "Anxiety, panic and self-optimization: Inequalities and the YouTube algorithm". *Convergence: The International Journal of Research into New Media Technologies*. vol.24, iss.1, 10 January.

⁶⁹ Kaiser, Jonas and Adrian Rauchfleisch (2018) 'Unite the Right? How YouTube's Recommendation Algorithm Connects The U.S. Far-Right' *D&S Media Manipulation: Dispatches from the Field* on Medium, 11 April, https://medium.com/@MediaManipulation/unite-the-right-how-youtubes-recommendation-algorithmconnects-the-u-s-far-right-9f1387ccfabd.

⁷⁰ Kaiser and Rauchfleisch (2018).

extreme content, (discussed further in section 5.2.4) but *why* the outcomes of recommendation seem to especially promote right-wing content requires investigation.

However the same epistemological problem of the unknowability of algorithms occurs again here. Mathematician Emily Bell highlights a moral implication of the black-box in that "when humans discriminate, there's usually a paper trail or a replication of behaviour," and that discriminatory, or hate-fuelling recommendation patterns are far more obscured than patterns of human behaviour.⁷¹ Auditing specific instances of far-right recommendation, as in Kaiser and Rauchfleisch's work, demonstrates dangerous patterns but does not, in itself explain them. Therefore, researchers are forced to take the broader perspective of analysing the teleological principles of recommendation algorithms:

So, turning toward literature which aims to explain dangerous recommendations, Lauren Bryant suggests "racist content equating to increased ad clicks"⁷² occurs because the YouTube recommendation algorithm "found an unexpected relationship between racism and the right amount of curiosity that prompts a person to continue to watch YouTube videos".⁷³ And this logic of interaction describes Facebook's recommendation algorithm, too, according to the company's leaked internal documents explored by Jeremy Merril and Will Oremus in *The Washington Post*.⁷⁴ The rare peek into at least the outermost layers of the black box, finds that algorithm ranking preferred 'angry' reactions over a 'like' and that users reacting to posts with negative emotions "would make Facebook show similar content more often".⁷⁵ As such, social media technoligopolies find themselves recommending extreme content not incidentally, but specifically because of its extremity, and a user's adverse reaction to that extremity.

In the same vein, Laura Edelson et al found that on Facebook, "misinformation generates more engagement," "particularly on the far right".⁷⁶ To this research, spokesperson for the company, Joe Osborne, responded that the study's measure of engagement was a poor proxy for actual viewership, which is nautrally the case because the company "does not make [view-numbers] available to researchers."⁷⁷ Facebook also disabled the researchers' accounts⁷⁸ over data collection "compromising people's privacy," as another example of the black box phenomenon, in this case being actively enforced by the company in question.⁷⁹

Further showing the combination of the themes of general extremification and selection for specific preferences, Bishop highlights the ubiquitous use of more extremely feminine tags on feminised content compared to the less explicitly gendered tags associated with male content.⁸⁰ Importantly, she links this unbalanced gender stereotype biasing to "the commercial nature of the women's tags," and the specifically advertiser-friendly showcase of makeup brands this genre involves, observing "that YouTube intentionally scaffolds videos consistent with the company's commercial goals".⁸¹

https://www.washingtonpost.com/technology/2021/09/03/facebook-misinformation-nyu-study/.

⁷¹ Bell, Emily (2016) 'Controlling the Unaccountable Algorithm', *BBC Radio* 4, 31 December.

⁷² Bryant (2020) p.90.

⁷³ Bryant (2020) p.87.

⁷⁴Merril, Jeremy B. and Will Oremus (2021) 'Five points for anger, one for a 'like': How Facebook's formula fostered rage and misinformation', *The Washington Post*, 26 October,

https://www.washingtonpost.com/technology/2021/10/26/facebook-angry-emoji-algorithm/.

⁷⁵ Merril, Oremus (2021).

⁷⁶ Edelson, et al (2021) p.455.

⁷⁷ Dwoskin, Elizabeth (2021) 'Misinformation on Facebook got six times more clicks than factual news during the 2020 election, study says', *The Washington Post*,

⁷⁸ Edelson, Laura and McCoy, Damon (2021).

⁷⁹ Clark, Mike (2021).

⁸⁰ An enlightening example of top tags on top videos by women: "'make-up', 'tutorial', 'routine', 'beauty', 'fashion', 'skin', 'drugstore' and 'cardio'" against men: "'funny', 'muscle', 'building', 'challenge', 'daschund' and 'Halloween'".

⁸¹ Bishop (2018), p.71.

In conversation with Emily Bell, Bernard E. Harcourt of Columbia Law School references the "rudimentary, but interestingly basic" pre-digital sentencing, parole risk-assessment, and contemporary predictive policing algorithms, such as that created by software company Hunchlab.⁸² These systems purport objectivity, in that they remove the nuanced human decision-making usually required in each of these situations. But building complex systems on the foundations of "very simple questions and factors" "present[s] problems and bias" and bake the creator's assumptions into inflexible mathematics.⁸³ While not driven by the same attention-economy profit motive as social media algorithms, or at least not so directly, the same process of codified bias applies, where following Safiya Noble's argument, "using historical data [means] forecasting some of these practices of the past directly into the future".⁸⁴ She notes that, inevitably, existing prejudices are "born out in the kind of data that is collected and created".⁸⁵

In *Algorithms of Oppression*, Noble dismantles the intuitive, but inaccurate, myth that recommendation algorithms simply reflect users' preferences back at them. "Marketing and advertising have directly shaped the ways that marginalized people have come to be represented by digital records" which are the foundation of algorithm decision-making.⁸⁶ This same principle works to explain right-wing biases in recommendation more generally; algorithms are informed by that information which already exists in historical records and conservative or reactionary politics are defined in large part by a preference for the past over the present. Reflections display reality in real time, where personalisation is built on datasets which Noble suggests are often outdated. Another flaw in the analogy that algorithms simply reflect preference is that personalisation systems bear out an ulterior motive that mirrors do not: the longer a user stares into the glass of their phone, the more profit can be extracted by showing them adverts.

As well as being the result of implicit bias in existing datasets, promotion and demotion of content can also occur directly. In 'Beyond the Black Box' by O'Dair and Fry propose a new categorisation of the "range of subtle practices" that determine content visiblity, including both explicit and implicit reasons for media recommendation bias.⁸⁷ These practices are grouped into 5 different types. They discuss how content might be given a "public upgrade", directly pushed to users, for example be having it "appear on the interface homepage," or the inverse in a "public downgrade". Content might also receive what they call a "shadow upgrade" and "become more likely to be selected within algorithmically-generated" playlists, as well as the inverse in a "shadow downgrade".⁸⁸ These public and shadow downgrades to content are opportunities to limit content exposure short of an "outright ban" of the content itself, similar to the tactic YouTube uses regarding what they call "borderline content" which "brushes up against the policy line but does not cross it".⁸⁹

But their 5-tier approach is too-blunt still. Though their discussion of the similarities and differences between bans, shadow bans, and visibility upgrades and downgrades provides important nuance, it falls foul of a base assumption. 'Upgrade' and 'downgrade' are both relative terms which presuppose a hypothetical neutral, default state in which media on 'algotorial' platforms are simultaneously being presented to users while neither being promoted nor demoted. But there is no such neutral state; the notion itself is flawed. All content shown to users by a recommendation algorithm is being

recommendation systems upon artists', Popular Communication, 18:1, p.65-77.

⁸² Bernard E. Harcourt interviewed in Emily Bell (2016).

⁸³ Bell, Emily (2016).

⁸⁴ Noble, Safiya (2020) 'Algorithms of Oppression: How Search Engines Reinforce Racism - Dr. Safiya Noble', Ai4, YouTube; https://www.youtube.com/watch?v=7AHv6vUouU8.

⁸⁵ Noble (2020).

⁸⁶ Noble, Safiya (2018) Algorithms of Oppression: How Search Engines Reinforce Racism, NYU Press, p.6.

⁸⁷ O'Dair, Marcus & Andrew Fry (2020) 'Beyond the black box in music streaming: the impact of

⁸⁸ All references to O'Dair, Fry (2020) in the paragraph cite p.72.

⁸⁹ YouTube, 'Does YouTube contribute to radicalisation?'.

https://www.youtube.com/intl/ALL_uk/howyoutubeworks/our-commitments/curbing-extremist-content/ #curbing-borderline-content.

recommended by definition, which in itself is promotion. There is no function on Spotify to shuffle its "100 million"⁹⁰ songs to users at random because the platform, like all algorithmic media platforms, is, first and foremost, its recommendation algorithm. There is no way to engage with YouTube's content without engaging in its algorithm, nor Facebook, nor Netflix, even when trying to find content directly, as "even search [...] becomes a recommendation".⁹¹ Siles's first-time TikTok users recognised this intuitively when they began to "use "TikTok" and "algorithm" almost interchangeably, consistent with a view of TikTok [and algorithm platforms generally] as an assemblage, an inseparable tissue of relationships between app, algorithms, and users".⁹²

At the most fundamental level, there is no way to navigate from one video on YouTube to another without passing through the membrane of algorithmic recommendation. Every user interaction with content on these platforms is mediated by recommendation algorithms, and therefore every interaction is implicated in the inherent political biases that stem from a system built around a telos of user retention and profit. As demonstrated by this discussion of the political outcomes of recommendation algorithms: not every recommendation drives users towards dangerous, radical content, but every recommendation is driven by a system which, overall, does.

⁹⁰ Spotify Newsroom 'About Spotify' https://newsroom.spotify.com/company-info/ accessed 14/01/2024.

⁹¹ Basilico (2019) 2:30-2:40.

⁹² Siles et al (2022) p.8.

Methodology

3.1 Broaching the black box

Studying any contemporary algorithm raises the black box problem (see section 2.1). As discussed above, my approach is informed by Bucher's research, and specifically her articulation that researchers should not expect the answer to be inside the black box.⁹³ Analysing the inner workings of algorithmic systems, industrial secret-sauces sealed from view or any other mode of measurement, presents an epistemological problem. This black-boxing is enforced intentionally by data corporations as "trade-secret protection". But deeper than that, "due to the technical necessity of handling the complexity of the system," algorithms' insides are unknown even to the engineers behind them.⁹⁴ This black boxing of the issue accounts for the previously described gap in the literature.

Indeed, as algorithms become more central to our societies, they seemingly only become further concealed from view. That security may get exacerbated: When Twitter moving its previously openaccess Application Programming Interface (API) behind a prohibitively tall paywall,⁹⁵ this change eliminated a whole subculture of hobby-coded reply-bots, de-prioritised against the perceived necessity of keeping even just endpoint information out of reach for analysts, especially seeing as the previous policy had been an industry aberration while it existed.⁹⁶ And while the Facebook's backroom data has never been actually public, Laura Edelson and Damon McCoy, algorithm researchers investigating the prominence and promotion of radical misinformation, had even their academic access to platform data rescinded, for a particularly forthright example of black boxing.⁹⁷ In this case, Meta had "invited" research on the condition the company "provide privacy-protected APIs and data sets," rather than allowing unfettered access, essentially asserting the contents of the black box without ever actually opening it to observation.⁹⁸

As such, my methodology of studying recommendation algorithms is to analyse the visible, user-end outputs of one specific algorithmic system — YouTube, specifically (see section 3.2) — and use a framework of algorithm studies theory to extrapolate the tendencies of media recommendation and their inherent politics (see section 5). By limiting the complexity of the system's inputs with simple proxies, assessment of the outputs will allow approximate evaluation of the 'decision' making process inside the black box. And the extent to which these results are traceable out from the corporate telos of retention maximisation for profit will define their usefulness in describing the broader process of social media recommendation logics in general.

3.2 Case study requirements

Needing a single system to test on, I chose the YouTube recommendation algorithm for a combination of 6 reasons:

⁹³ Bucher, Taina (2016) Neither Black Nor Box: Ways of Knowing Algorithms. In: Kubitschko, S., Kaun, A. (eds) Innovative Methods in Media and Communication Research. Palgrave Macmillan, Cham.

⁹⁴ Bucher, Tania (2018) *If... Then: Algorithmic Power and Politics*, Oxford University Press, p.42.

⁹⁵ Stokel Walker, Chris (2023) 'TechScape: Why Twitter ending free access to its APIs should be a 'wake-up call'' *The Guardian*, 7 Feb 2023, https://www.theguardian.com/technology/2023/feb/07/techscape-elon-musktwitter-api.

⁹⁶ Most major platforms don't have public APIs, and those that do guard access thoroughly: e.g. Instagram only made their API public-accessible in 2021, and even then the process is arduous, requiring video-requests for each separate permission. See: *Meta for Developers*.

⁹⁷ Edelson, Laura and McCoy, Damon (2021) 'We Research Misinformation on Facebook. It Just Disabled Our Accounts,' *The New York Times*, 10 August, https://www.nytimes.com/2021/08/10/opinion/facebook-misinformation.html.

⁹⁸ Clark, Mike (2021) 'Research Cannot Be the Justification for Compromising People's Privacy,' *Meta*, 3 August, https://about.fb.com/news/2021/08/research-cannot-be-the-justification-for-compromising-peoples-privacy/.

Firstly, the platform's primacy. YouTube is one of the biggest social media platforms in the world, with more than two billion users globally.⁹⁹ As a central pillar of the social media industry, then, YouTube both represents a median and accepted system with a globally representative and approximately politically average user-base, rather than fringe and unrepresentative platform such as Parler, which has stronger political biases and more obscure structural organisation.¹⁰⁰ The scale of YouTube also means that there is a wealth of existing literature and comparable experiments on the platform.

Secondly, YouTube is, currently, relatively stable. Unlike other platforms, whose moderation, recommendation systems, and even corporate names are in constant and often erratic flux, YouTube's core practices have remained comparatively broadly steady since its adoption of machine learning recommendation in 2016.¹⁰¹ It is an under-discussed aspect of the black box problem that as well as being intentionally unknowable, the contents of the black box are in a continual and continually concealed state of change. All algorithmically driven platforms are always in the process of developing their practices, as recommendation itself is a fast-changing process. However YouTube's resistance to the more volatile change experienced by other platforms means that relevant research remains relevant for longer. It means that it is practically possible to plan and execute experiments on the platform, and that my findings are born out of algorithmic recommendation operating as normal, rather than representing an aberrant example of algorithmic behaviour.

Thirdly, Bucher suggests that researchers understand the black box by studying its outputs. To that end, the YouTube recommendation algorithm has an extremely clear and outwardly algorithmic output in the form of its sidebar of recommended videos under the subtitle 'watch next'. Here, the platform holds user agency and algorithmic curation in tension: theoretically, what the user watches next is a choice, and practically, that choice is only from a range of predetermined predictive options.

Fourth, on the platform's 'autoplay' mode, these recommended videos are queued algorithmically. 'Autoplay' is enabled by default on the platform, which Bryant notes is "an issue in itself with consent"¹⁰². This "infinite scroll" is a ubiquitous feature of algorithm media ecosystems, and, on YouTube, explicitly the intended logic of user engagement.¹⁰³ Hence, my study is not prodding unexpected outcomes of marginal features. Rather, I am measuring the ordinary outcomes of the encouraged logic of use.

Fifth, YouTube's ability to provide a constant, singular stream of new content to the user is practically helpful. The 'autoplay' function allows me to remove methodological interference of my own taste or invisible biases that would impact the results on a platform where interaction was required. Instead, the case study can be constructed in such a way as to be insulated from any impact my interaction with the recommendation system might generate. Limiting my accidental impact on recommendations is as important as it is difficult, given that even the movement of the cursor across the webpage can be processed as behavioural surplus.¹⁰⁴

Sixth, and finally, part of the reason for its active user base of approximately a quarter of the population of planet earth¹⁰⁵ is the platform's audience of adolescents and, often, infants. "For hours

⁹⁹ YouTube has 2.6 billion users according to *Kepios* analysis of platforms' self-service advertising resources in their 'Digital 2023: global overview report,' 26 Jan 2023.

 ¹⁰⁰ Paul, Kari (2023) 'Parler: the social network that's winning conservative recruits,' *The Guardian*, 13 Nov 2020, https://www.theguardian.com/media/2020/nov/13/parler-conservative-social-network-free-speech.
 ¹⁰¹ Covington, Paul; Jay Adams; Emre Sargin (2016) 'Deep Neural Networks for YouTube Recommendations', *Google Research*.

¹⁰² Bryant (2020), p.86.

¹⁰³ Collins, Grant "Why the Infinite Scroll is so addictive," UX Design, 10 Dec 2020, https://uxdesign.cc/why-the-infinite-scroll-is-so-addictive-9928367019c5.

¹⁰⁴ Wilson, Dean (2010) 'Google nabs patent to monitor your cursor movements' *Tech Eye*, Archived from the original on 22 March 2014 via *The Internet Archive*.

¹⁰⁵ Though it is worth noting *Kepios* are unable to exclude verify unique ownership of the account. In fact, the many virtual accounts I have created in the process of this research, either for the detailed case study or other

and hours and hours" YouTube's effectively infinite source of auto-playing entertainment acts as an audio-visual pacifier which "hack[s] the brains of very small children in return for advertising revenue."¹⁰⁶ That infants can use these systems, or rather have these systems used on them, indicts YouTube on the issue of user agency. Any notion of this relationship being based in informed consent can be disregarded here. Where many social media algorithms require a level of input from the user to guide recommendations, YouTube recommends to users literally incapable of steering away from harmful content. Those most vulnerable to possible malign online influence are those interfacing most directly with the raw telos of the system. This logic of interaction is the model of my case study.

3.3 Case study methodology

3.3.1 Pilot

My approach to generating a dataset that could be used as a case study for my analysis was to click on a YouTube video and let the system work. I would begin auto-playing YouTube videos, allow the recommendation and auto-playing cycle to repeat many times, and assess the results. My foremost aims were to maximise the impact of the recommendation algorithm in selecting media and to minimise my own interactions with the process. These conditions would create a dataset that gave primacy to algorithmic tendencies, which were ideal for analysis, as it is the algorithmic system itself, rather than the logic of interactions with it, with which this case study is concerned.

I first constructed a 'pilot' case study of the above methodology to test its robustness. Running this pilot, and then later the case study itself, I created a number of proxy YouTube accounts for fictional users with no existing watch-history. These had to be mastered by new Google accounts, so as to, as far as possible, avoid stepping on or contaminating the proxies with my own existing data footprint. By using proxy accounts of much more limited complexity than real, historied users, I reduced the complexity of input to the black box of algorithmic 'decision-making', therefore allowing a cleaner analysis of the process generating its recommendation outcomes.

However, two problems presented themselves: First, within the parameters of practicality, clinical decontamination was impossible — data is collected on IP addresses, for example. Additionally, after creating the first few user accounts for this pilot, the 'new account creation' page changed to require phone number verification, meaning yet more contaminating data on the fresh accounts. Presumably this was a result of creating new accounts from the same IP address, a deterrence against sock-puppets and bots.

The second problem was that, left on autoplay, without direct intervention, the stream of autoplaying YouTube videos trend longer, fast. For example, one test account began with a ten-minute video from GBNews, but within only five autoplays was already being shown videos longer than an hour, and within a couple more, videos literally undetermined in length: livestreams. This was my first finding, before the case study itself even began, and it would go on to be central to my analysis (see section 5.2.1). But it posed obvious practical issues for the construction of the case study. This overwhelming bias towards, and persistent autoplay of, extremely long-running content and livestreams meant no further videos would auto-play. Effectively, the virtual accounts would get stuck.

To counter the impractically strong bias toward increasingly long-runtime content, I gave each account in the case study itself the same bias towards short content by immediately skipping any content longer than an hour. As well as being just a practical way of avoiding these unworkably long videos, the skipping should theoretically also have imparted a preference that the algorithm would reflect back, resulting in shorter recommendations overall. This attempt to steer the algorithm towards

tests, would count towards this number despite not representing a unique user. However, given the number of users sharing accounts (especially children using parents') it seems fair to accept the approximate figure as broadly accurate. Certainly it would need to be to be useful to advertisers.

¹⁰⁶ Brindle, James (2018) 'The nightmare videos of childrens' YouTube — and what's wrong with the internet today | James Bridle', *TED*, YouTube, 13 July, https://youtu.be/v9EKV2nSU8w.

shorter videos, however, didn't stop the recommendation of videos over one hour in length. Skipped videos were still recorded (see Appendix), given they were recommended by the algorithm, and I returned to those >1hr videos after the completion of the case study itself, to analyse their content.

3.3.2. Case study

For the case study itself, I created 3 fresh YouTube user accounts each with a simulated existing bias.

Bishop highlighted the significance placed on gender and gender polarity especially by the YouTube recommendation algorithm,¹⁰⁷ and as such, I left the gender of each virtual account undisclosed. Because an actual 2-part name is required to create a Google account, simple pseudonyms not permitted, I picked three gender-neutral ones: Ash Aarons, Bobby Babbage, Charlie Callaghan.

I assigned Ash political neutrality, disengaged from polar politics, Bobby, a right-of-centre bias, and Charlie, left-of-centre. These representations of a variety of existing views provides a measuring stick for the power of the algorithm's impact compared to the initial conditions of the user's political views. Ash represents the pure action of algorithmic recommendation, and should, like a compass, point towards the system's telos. Bobby and Charlie introduce the friction of a genuine user, the complications of existing tastes, but also present an opportunity for the algorithm to demonstrate personalisation in action in the simplified setting of fictional users.

While my aim is not to find direct evidence of the preponderance of radical recommendations as described by other researchers, assigning Bobby and Charlie oppositional political preferences provides the opportunity to observe subtler differences in patterns of recommendation on the basis of existing politics. This thesis explores the logic of the unextraordinary recommendations, and searches those commonplace interactions for the underlying logic which results in the extraordinary outcomes of radicalisation. By differentiating Bobby and Charlie along a linear polarity, their preferences also foster a number of corresponding algorithmic assumptions noticeable in the resulting data, such as an age differences between these two non-existent users (see section 5.2.3). However, while not the focus of this study, the political polarity of Bobby and Charlie's preferences here nonetheless presents an opportunity to reinforce the findings of prior literature (see section 2.4): first, to what extent radical recommendations can be observed, and second whether any such content is promoted equitably in different political directions.

Encoding Bobby's and Charlie's biases required training. I gave both accounts a playlist of videos from a news provider corresponding to their bias. Bobby watched *The Daily Mail* and Charlie *The Guardian*. These playlists were each several hours and dozens of videos long and covered a random spread of reporting of and commentary on contemporary news issues. I chose playlists on random topics to avoid priming either account with a preference for a specific topic. Instead, this training created two personas with media habits representative of broad perspectives of political alignment. Ash underwent no prior preference training at all, so that when the case study began the account would engage with the algorithm as a total neophyte. As such, Ash provides a clean demonstration of how algorithmic recommendation functions, and what end goal its recommendation trends towards, unencumbered by the perceived preferences of a user.

The three accounts were then given starting videos, reflective of their biases, on the same topic, so as to assess topic variance comparably across the accounts. For this shared starting topic I chose coverage of the 2022 world cup final in Qatar, which was contemporaneous at the time. It set the three accounts off from different videos on the same topic so as to have a common starting line in terms of topic, while preserving the personas' existing preferences. From this starting line, I could compare the ways in which the accounts diverged (or didn't) into different topics and types of content.

The world cup final specifically made for an appropriate starting point because of its international scale and cross-cultural relevance. The popularity of the event in the UK ensured there would be plenty of coverage by different outlets across a range of political perspectives and related content for the algorithm to recommend to the users. Similarly due to its widespread popularity, relative to other

¹⁰⁷ Bishop, Sophie (2018).

topics, interest in the world cup final implies little about the users that might impact future recommendations.

Ash began the study itself with a video direct from FIFA itself: *THE GREATEST FINAL EVER?!* | *Argentina v France*. Bobby's starter was *The Daily Mail, Argentina vs France reaction: Journalists react to sock Martinez antics* | *World Cup Confidential*. Charlie's was *The greatest World Cup final of all time?* | *Football Weekly Podcast* | *Argentina vs Frace Reaction*, from *The Guardian*. I ran these accounts' video-binge in succession, rather than continuously, to allow for the recording of ephemeral data which would not be naturally remembered by watch history, or verified by returning to the videos later. It also allowed me to pay close attention to each recommended video as it was played, rather than sorting through the videos after the fact.

From this starting point, autoplay took over, and videos were selected by the algorithm. I allowed these video streams to run all day, until each account reached its 20th video played in full (in other words, the 20th video under 1hr in length). In the case of Ash I recorded a further 5 videos to ensure for definite a large enough dataset. While the number of iterations, and thus the scale of the case study, was limited by feasibility, Kang and Lou found that similar algorithms "can learn the vulnerabilities and interests of a user in less than 40 minutes". Each video stream reached 40 minutes in length in just a few recommendations, coming to a total of 4hrs 32min (Ash), 13hrs 22min (Bobby) and 12hrs 31min (Charlie). As such, 20 iterations provided more than enough qualitative information and early indications towards broader trends.¹⁰⁸

I played videos shorter than an hour all the way through so as to assess their qualitative content, but also because watch-time is measured as to assess user 'engagement' and impacts recommendations. I returned to skipped videos later and, where possible, completely watched them too. I recorded the information about each autoplayed video into 3 categories (see also Appendix):

- a) Video data (runtime; video titles; views)
- b) Channel data (channel name; content focus; notable politics)
- c) Subjective analysis (topic; tone; content; notable recommended)

In the third of these categories, I have made subjective assessments of tone and content, especially in regard to politics, extreme views, misinformation, and related themes. While it's difficult to apply the same observational criteria to a stream of videos containing documentaries, albums, sports, and vlogs alongside one another, I derived a number of criteria to judge recommendations on. I assessed videos with factual claims on their accuracy, as well as their presentation of information, with particular attention to misleading or exaggerating 'clickbait' claims, titles, and thumbnails. I assessed a video's tone from formal to informal and from impassive to passionate, as well as noting other significant information, or specific politics, such as a documentary video misrepresenting evidence or a partisan political framing. I included here even minor, implicit political content, such as Bishop's indicators of highly gendered content, for example. I also assessed the topics of videos in their own right by placing them in the broader contexts of the publishing channel's other works. After generating the datasets, in the process of reviewing the videos recommended to each proxy, I visited the channels hosting the recommended videos and assessed the channels' other outputs, watching other videos where relevant.

I then look across this dataset to discern patterns between video recommendations and developments in each account's recommendations over time, as well as highlighting specific outstanding examples of recommendation. I then cross-reference these patterns, developments, and outstanding examples across the three accounts to assess the impact of existing user preferences on recommendation.

So, looking to the results, I aim to answer three primary questions from the data:

¹⁰⁸ Kang, Hyunjin and Lou, Chen (2022) 'Al agency vs. human agency: understanding human–Al interactions on TikTok and their implications for user engagement', *Journal of Computer-Mediated Communication*, vol.27, iss.5, p.4.

- 1. What patterns emerge in the form of recommended media, especially reflective of the algorithmic telos of user retention?
- 2. What patterns emerge in the content of recommended media, especially in regard to extremification or specific political bias?
- 3. How do the answers to questions 1. and 2. interface with one another?

By elucidating the formal factors prioritised by the recommendation algorithm and linking those to the extreme, misleading, or political polar content of recommended media, I will answer the thesis research question: *how does the algorithmic telos cultivate radical political outcomes by its recommendation of media?* Analysing how these patterns relate to extreme content, the thesis will in doing so draw a causal link between the fundamental driving force of algorithmic recommendation and the system's dangerous outcomes.

Observations

4.1 Formalities

The case study generated the thesis's dataset in the form of three playlists of watched videos, one from each of the users, which will be referred to as 'recommendation streams' (see Appendix). Each simulated binge-watch covered a minimum of 20 recommended videos under an hour in length, and accounting for the great number of recommendations longer than an hour, this makes a total of between 52 and 123 overall recorded recommendations per stream. I force-skipped every video over an hour in length, so as to avoid the exponential-growth in recommended-video-length that pilot case study discovered (see section 3.3.1), I also recorded analysis of those skipped videos by revisiting them after the initial data pool had already been generated.

For brevity, I will refer to videos by a letter-number combination (e.g. *A12*), the first describing the user (e.g. *A* for *Ash*) and the latter describing its position in the respective recommendation stream (e.g. *12* for the 12th autoplayed video, including those skipped) for simple reference to the details of that video recorded in the attached appended data sheets. The linear list of recommendations received by each account, as well as some observations around those recommendations, are provided in the form of spreadsheets, and are not the method by which I approach these findings. Instead, I explore the findings in the broad patterns of each user's recommendation stream and how it developed through the case study; in themes that cut across the three streams, highlighting similarities and differences in recommendations; and with some in-depth reference to particularly noteworthy videos and instances of recommendation.

4.2 Surface findings

4.2.1 Erraticism and unpredictability

The most evident immediate finding of this case study is that the political bias training undergone by Bobby and Charlie had an enormous impact on their recommendations relative to the impact on the recommendations to Ash, the account account with no training whatsoever. However, the polarity of Bobby and Charlie's oppositional bias training had a much more subtle impact on their recommendations relative to the one another. In other words, the two accounts with a political bias, regardless of polarity, saw a pattern of recommendations more visibly similar to one another than to the 'neutral' account which was positioned theoretically between them on a political axis.

While these findings show some trend towards extremification over time, as per previous research (see section 2.4), the general progression of of recommendations throughout Bobby and Charlie's streams is much more erratic than a straightforward 'radicalisation pathway'. There is an extreme variance in the topic, tone, and political content of the recommended media for these two proxy users. At some points recommendations are completely erratic, jumping from topic to topic video by video with no clear connection between content. For example, C5 is a live-streamed football match, C6 is a 'tier list' video ranking book cover variants for the *A Song of Ice and Fire* series, and C7 is a video-gaming news and review podcast. More often in the data, this erratic recommendation results in strings of a dozen or so clearly related videos focussed more or less broadly on a particular topic, before jolting to another topic not directly related to the prior. For an example of this pattern: C36-46 is a string of videos of football and football-focussed commentary, and C47-52 is a string of Christian sermons and worship music. While evidently extremely unpredictable, some rationale for such erratic recommendations can be found by taking a wider perspective.

Viewing the generated recommendation streams more broadly, worship seemed to enact a particular algotorial gravity, for Charlie in particular, with the algorithm first autoplaying Christian media at C47, seemingly unrelated to the previous run of football videos and commentary. The recommendation stream then autoplayed relaxation music (C55-67), then jukebox pop compilations (C68-80) before returning to sermons and worship for the remainder of the case study (C81-123).

Similar patterns are visible in Bobby's recommendations, which became quickly overwhelmed with television and direct-to-YouTube documentaries of variable topic and veracity. In direct terms of the media's content, this pattern of recommendation was unrelated to either to Bobby's starting video or their prior training. For example, iterations B36-38 of Bobby's stream transition from an ecological documentary,¹⁰⁹ to an episode of reality TV building demolitions,¹¹⁰ to a science-history documentary.¹¹¹ The actual content, topic, and tone of these videos vary wildly, and an actual user is very unlikely to have an active interest in all three areas, and certainly to feel that each is a natural progression from the former. But the three videos share a through-line of formal qualities: in terms of genre, all three videos are documentaries, of different kinds; in terms of runtime, each video is a feature-length production, covering the whole spectrum of the definition of the term (the shortest video being 47 minutes, the longest, 2 hours 57 minutes); and each video originated in the television format (C36 on Nova PBS, C37 on National Geographic and Five, C38 on the BBC).

4.2.2 Ash and the neutral centre

Bobby and Charlie's recommendations quickly skewed in topic away from the World Cup, then football generally, then sports altogether. Conversely, Ash's recommendation stream and auto-plays are notable for never once straying from the official FIFA channel. Every autoplay and almost every high-level recommendation on every video provided Ash with more of the same content: direct footage from football games and major tournaments, all on the FIFA YouTube channel. These were split almost down the middle between highlight reels and full matches (all of which were skipped, being longer than an hour), with 25 full matches, 22 highlights edits, and 5 documentary or commentary videos. As well as only recommending content from one channel, the algorithm also recommended videos overwhelmingly of one specific form: direct footage from football games with little additional commentary.

The only time this pattern of strict adherence to topic broke even remotely were to this were two consecutive video documentaries on Lionel Messi and Cristiano Ronaldo respectively (A30, 31), and even these were largely comprised of highlight reels and historical goals. These were the only two videos recommended to Ash which constituted the same kind of commentary that made-up the majority of the other two accounts' video streams.

In terms of *political* content, Ash's videos didn't just remain neutral, but were uniformly barren of observable political content whatsoever. If there is any extremification effect on display in this video stream, it is not in the form of the outright recommendation of politically extreme content from a neutral starting point.

4.2.3 Similarities between Bobby and Charlie

Despite theoretically oppositional training, as a proxy for theoretically oppositional existing personal views, Bobby and Charlie were subject to recommendations with more commonality, both on the level of individual videos and broad trends, than either shared with Ash. One such commonality is that both auto-play-lists immediately diverted from news coverage of the World Cup into podcasts.

Bobby's recommendations began with 16 shows (B3-18) from *Off The Ball*, an Irish radio daily sports show with a video version uploaded to YouTube. After video B18, Bobby was now being recommended rugby commentary instead of football, from *The Good, The Bad, and the Rugby* first to *Rugby Pass* later on. Although focussing on different sports, these channels are similar in their form as conversational video sports commentary. While Charlie's recommendations were a more eratic, their recommendations also centred on a sports commentary podcast, in this case *In Soccer We Trust*. In Charlie's case, the autoplay process returned to this podcast even after diverging into different content, pinging pack to the topic from unrelated media. Charlie's 35th video (C35) is a VR-specialised computer-game awards show by channel *Virtual Strangers*, and its 36th (C36) is roster

¹⁰⁹ Arctic Sinkholes | Full Documentary | NOVA | PBS.

¹¹⁰ Monster Tower | World Record Building Demolition | Blowdown.

¹¹¹ Shock and Awe: The Story of Electricity -- Jim Al-Khalil.

predictions by *In Soccer We Trust*. I discuss the significance of the differences between these two podcasts as the primary recommendations to Bobby and Charlie (see section 5.2.3), but these videos from *In Soccer We Trust* and *Off the Ball* have clear similarities in terms of shared formal features, much the same as *Rugby Pass* and *The Good the Bad and the Rugby*.

Both Bobby and Charlie began with World Cup coverage and were recommended popular podcasts following their original videos of World Cup news coverage, with only subtle differences between them. After these parallel forays into popular football podcasts, Bobby and Charlie's recommendation feeds diverge radically from one another as their recommendations become increasingly niche. Following *The Phenomenon* (B23) Bobby's recommendations consist only of documentaries, professional and amateur, grounded and ungrounded alike. Charlie's show more fluctuation, returning to the topic of sports (C36) after exploring gaming culture and before diving headlong into worship music and sermons for the remainder of the runtime.

It's also worth noting explicitly the similarity that several of the YouTube channels hosting documentaries in Bobby's recommendation stream, and music compilations in Charlie's, are not publishing unique content created by the channel, but rather recycling copyrighted content in bulk.

4.3 Extremes and niches

4.3.1 Bobby and the UFOs

After 22 videos of sports coverage, Bobby was recommended and so auto-play-ed *The Phenomenon*, (B23) a 2020 documentary film by James Fox about the alleged cover-up of UFO sightings by the government of the United States. This was followed by the recommendation of eleven more ordinary documentary films (B24-34) on a range of topics, which varied in source and credibility. For example, the sensationalist presentation of documentaries such as *The Unsolved Mysteries of Jesus Christ* (B34) deploys some of the same rhetorical tricks as *The Phenomenon*, as I will discuss. After these 11 documentaries, Bobby was recommended *The UFO Phenomenon*, a documentary on the same topic as *The Phenomenon* with similar problems regarding misinformation and deceptive presentation.

While largely avoiding outright disinformation, these films engage in misleading framing and use leading rhetorical devices to make their argument. To use The UFO Phenomenon as my example: Immediately following the opening credits, the introductory sting presents digitally generated videos of UFOs paired with actual audio from alleged military encounters with unexplained phenomena without clearly signalling the artificial nature of the footage (2:10-2:40). Following this introduction, host Ross Coulthart describes the "UAP task force" operating "secretly" out of the pentagon "investigating the phenomenon of UFOs, flying saucers, strange craft in our skies" (3:30-3:50). Here, the documentary subtly equates Unidentified Anomalous Phenomenon (UAP), used to describe any unexplained aerial incident, with three related, but significantly non-identical terms: 'UFO' is a similar initialism to UAP, but with stronger associations with alien folklore and imagery; 'flying saucer' is a specific claim as to the nature of a phenomenon, further associating unknown phenomenon with existing folklore; and describing UAPs as 'strange craft' is a direct assertion that the unknown phenomenon is in fact a spaceship of some description. To a lay viewer, this sentence and rhetorical flourishes like this throughout the documentary would seem to confirm that the US government has a secret task force devoted to alien space ships. The documentary is primarily comprised of a series of interviews with and anecdotes from individuals sharing 'encounters' with unidentified phenomenon of various kinds, and concludes with one such interviewee suggesting "you're crazy if you don't ask questions" (1:18:00). In the same spirit, The Phenomenon "ultimately can't stake a claim on certainty,"¹¹² but frames its asking of questions through the lens of a director "absolutely convinced that these objects are real".¹¹³ Reviewers described some of the documentary's

 ¹¹² Horton, Adrian (2020) "It's not a question of belief': the film examining government UFO records', *The Guardian*, https://www.theguardian.com/film/2020/oct/07/the-phenomenon-ufos-james-fox-documentary.
 ¹¹³ Fox, James interviewed in Horton, Adrian (2020).

leading "suggestions" as "dubious, if not outright dangerous", because by leaving viewers without answers, this recommendation may also lead users towards more niche UFO media containing "rampant conspiracy theories, which often invoke the military and/or space".¹¹⁴ This tendency of algorithmic recommendations to guide users from more reliable to less reliable content is discussed in depth in sections 5.2.3 and 5.2.4.

The channel publishing *The Phenomenon* is called *UNIDENTIFIED*, and also posts documentarystyle videos on cryptids ('Aliens at Loch Ness'), ghosts ('Afterlife Investigations') and more generalised conspiracy ('Yes They Are Controlling Our Minds' and 'Third Eye Spies').¹¹⁵ YouTube's recommendation algorithm began recommending this conspiracy theory content both suddenly, with no clear link to the previous recommendations, and routinely, as one of many TV documentaries recommended in series. Later recommendations (B63, 64) were unremarkable geography documentaries, but hosted on a channel (*hazards and catastrophes*) similarly rife with conspiratorial misinformation, including videos on mind control and the illuminati (*Illuminati: Myths and Realities of a Parallel World*).

4.3.2 Bobby's history documentaries

Outside of these outstandingly outlandish recommendations, the remainder of Bobby's video stream after moving on from football (B23-71) was comprised entirely of low budget television or straight-to-YouTube video documentaries. Here, recommendations seemed to lock in to a specific genre or form of media, which I describe as the algorithm finding a niche for Bobby (see section 5.2.3). Once settled into that niche, Bobby's recommendations didn't shift away from it for the rest of the runtime of the case study.

While there is a visible uniformity in terms of the formal features of these media recommendations, the a niche is less specific in terms of the videos' content, though some patterns still exist. First Bobby was recommended pop-scientific overviews, usually on topics of physics and astronomy, like *Mind-Blowing Facts About our Reality [4K]* (B31) or *Harnessing The True Power of Atoms* (B32). *The UFO Phenomenon* and *The Phenomenon* also fit loosely into this category. Later, recommendations shifted towards historical documentaries, with a focus on wartime history, such as *How Did Britain Build More Airplanes Than Germany in WW2* (B60). In so much as there is a pattern in the content and political qualities of these history documentaries recommended to Bobby, they are generally group-able into 5 categories: 'the natural environment' (B36, 63, 64). 'inventors and engineering' (B38-45, 56), 'mysteries of the ancient world' (B45-49, 61, 62), 'warfare' (B51, 53-55, 57-60, 69-71), and 'exploration and colonialism' (B50, 65-67). Another way of grouping these videos is by their focus on individual historical figures; see: *How Leonardo da Vinci Changed the World* (B40) and *Benjamin Franklin - Founding Father of a Nation Documentary* (B67) as examples. Eleven of the recommended documentaries are about one specific individual. All eleven are white men.

This pattern of recommendation evidently contains an implicit bias, but in some cases also an explicit political perspective. *Captain James Cook: The incredible true story of the World's Greatest Navigator and Cartographer* (B50) is an amateur Australian video documentary on the *Heroes and Legends Documentary Channel* arguing against the modern re-assessment of Cook as a historical figure in light of his role in the colonisation of Australia and the violence on contact with indigenous people and communities. The video's host argues in the opening sentence that "first nation people demand the rewriting of history" and want to "cancel" Cook.

While perhaps less controversial or explicitly reactionary in their outlook, a dozen of Bobby's recommended documentary videos proceed along the line of reporting and celebrating controversial historical figures. A particularly strong example is: *Lee & Grant - Worthy Adversaries Documentary* (B67), a comparative work between Robert E. Lee and Ulysses S. Grant. While theoretically balanced in its equal celebration of the unique military genius of the two figureheads of the American Civil

¹¹⁴ Horton, Adrian (2020).

¹¹⁵ "UNIDENTIFIED" on *YouTube*, https://www.youtube.com/@watchunidtv/videos accessed 10/09/23.

War its historical commentary also amounts to equating positions for and against slavery as if morally equal.

In this vein, Bobby was also auto-played *The Man That Confronted A Dictator* (B55), a documentary about WWII fighter pilot Günther Rall, who served in the Luftwaffe. The documentary carefully frames Rall's military achievements as separate from the politics of Nazi Germany, with Rall himself saying his service "had nothing to do with the [Nazi] party" (13:30). Claiming to "separate the army from everything that had to do with politics," (14:00) the documentary proceeds to straightforwardly celebrate Rall's career, and avoids the fact that Günther Rall "knew of the persecution of the Jews"¹¹⁶ Beyond the valorisation of war, that the military can be divorced from its political context is a particularly significant and political claim, similar to the treatment of Lee and Grant as rivals in an abstract, academic sense.

4.3.3 Charlie and the megachurch

Taken overall, Charlie's recommendations, compared to Bobby's seem immediately less radical. Certainly, the account wasn't pushed anything quite so extreme as UFO documentaries. Rather, 15 of Charlie's recommendations (C52-67) are made up of instrumental mediation music. With no lyrics, these complications of calm music taken out of its original context don't have any clear signifiers of politics or other significant content at all.

Following this, Charlie was recommended two full Led Zepplin albums (C68, 69) and a compilation of Pink Floyd music (C70). All three of these videos contained specific examples of songs with particular political themes, including *Misty Mountain Hop*, from *Led Zepplin IV* (C68) about a clash between police and students over drugs. Many of the Pink Floyd songs have specific political messages generally aligned with a left-leaning perspective. For example *Pigs (Three Different Ones)* (11:26-17:05) is a diatribe against "Steve Schwarzman" (and businessmen generally), "Margaret Thatcher", and "Mary Whitehouse", figures of economic, political, and social conservatism.¹¹⁷ The collection of songs also contains anti-war, anti-institutionalisation, and anti-consumerism themes. The following 10 video run (C71-80) of pop music compilations similarly contain songs with political themes and other notable content. However, these are abstracted out of their original context and diluted when mixed randomly together with other hits, such that I would not describe the compilation video itself as political.

However, following this run from C68-80, Charlie was recommended Christian worship music, and consequently evangelical sermons and church services, which then dominated the feed for the rest of the case study (C81-123). While the worship and sermons being recommended were rarely explicitly political in terms of the direct text, the recommendation of religious content is noteworthy in relation to the telos of the recommendation algorithm. Specifically, the recommendation of evangelical worship, often viewed as eccentric or particularly devoted compared to more mainstream Christianity, is part of an observed pattern of the recommendation of content in its most extreme, most dedicated form (see section 5.2.4). Videos such as *The Glory of Jesus* | *Michael Koulianos* | *Sunday Night Service* (C111) include claims of faith healing mental and physical illness (1:50:30). In the same service Koulianos (the pastor) asks viewers at home to be "wildly and extremely generous" in donating to pay off his church's debt (1:32:20) from the cost of the massive theatre's new sound system, and this relationship between media's aesthetic, audience-drawing qualities and its finances will be relevant to my analysis (see section 5.5)

¹¹⁶ Amadio, Jill (2002) *Günther Rall: A Memoir- Luftwaffe Ace & NATO General*, Seven Locks Press, p.263.

¹¹⁷ Rodger Stone interviewed by Kory Grow (2019) 'Roger Waters Talks 'Us + Them' Film, Why Pink Floyd's Songs Remain Relevant', *Rolling Stone*, https://www.rollingstone.com/music/music-features/roger-waters-us-them-film-interview-889933/.

4.4 Form vs content

4.4.1 Runtime tendencies

In designing this methodology, the greatest obstacle was the recommendation algorithm's preference for runtime, as shown in the pilot tests (see section 3.3.1). Looking at the data directly, the single most influential, and certainly the most obvious bias of the recommendation algorithm from this case study is that towards greater runtimes. So strong was this preference that it derailed every video stream by immensely slowing the flow of videos and eventually slipping into the recommendation of outright livestreams. Even biasing accounts against this tendency, actively skipping any video greater than one hour in length, YouTube continued to recommend videos longer — often much longer — than an hour. As such, all three users, apparently regardless of their training or artificial preferences to the contrary, were consistently pushed toward toward those videos of greater length.

In total, 180/246, more than two thirds, of recommended videos across all three streams were over an hour long, and independently, each individual account was autoplayed videos longer than an hour more often than those shorter. Out of 52 videos recommended to Ash, 27 were longer than an hour, with 50/71 for Bobby and 103/123 for Charlie. This shows a slightly stronger bias towards longer videos for the two accounts with simulated existing preferences and more erratic recommendation, than that for the account with no existing preferences.

The tendency towards longer runtimes is consistent with the telos of user retention, and through that, links to other patterns in recommendation. However, there are no clear correlations in the data between how long a video is and other factors such as its political content or topical extremity. Instead, the preference for longer content seems essentially consistent across the three users and throughout each of their recommendation streams, suggesting a primacy of the preference for runtime. This uniform formal trend towards longer content is perhaps the clearest overall finding of the case study, substantiating the claim of earlier literature that algorithms online exist to "keep you glued to your screen for another few seconds," or in this case, another few hours.¹¹⁸

4.4.2 Viewership and channel upload frequency

The viewership numbers of recommended videos varied to an extreme extent between single-digit thousands and double-digit millions. This is a range of 500x between the videos with the greatest viewership (at \sim 90 million) and those with the lowest (at \sim 3,000). None of the three avatars are recommended any videos with fewer than 100 views, which is notable as the majority of videos on YouTube belong in that category. Only one video was recommended with fewer than 1000 views (B21) and that was a notable outlier in that the video had been uploaded earlier that same day.

Evidently, the algorithm is not recommending videos at random, as recommending videos randomly from a pool with so many videos with so few views would result in a much lower average video viewership. But neither is it recommending the most popular videos or channels on the platform which, statistically speaking, are those a random user would be most likely to like, as they are already the most popular. A completely new user logging on to YouTube for the first time is shown a home page of the most popular content on the platform, which is not reflected in the recommendations given to Ash, Bobby, or Charlie. I argue therefore that the algorithm prioritises recommendations that are personalised to users' preferences even when it has only a few data-points as to those users' tastes, or even only one data-point, as in the case of Ash.

Therefore, even when the topic, genre, and medium of videos seem on the surface that they are being recommended at random and with no obvious connection, as in the case of Charlie, what seems like algorithmic noise is clearly still an attempt at personalisation. Logically, every bizarre recommendation Charlie received must somehow be the product of the limited preference training that the account underwent. Something links *The Guardian*, video-gaming, Rodger Waters and the gospel

¹¹⁸ O'Donovan, Caroline et al. (2019) 'We Followed YouTube's Recommendation Algorithm Down The Rabbit Hole', *Buzzfeed*, 24 January, https://www.buzzfeednews.com/article/carolineodonovan/down-youtubes-recommendation-rabbithole.

truth in the eyes of the algorithm, and whatever that link is, it has been selected for by the recommendation system.

4.4.3 Algorithmic genres

As discussed, there are few clear trends in these finds in regard to topic, with many sudden leaps of recommendation, and algotorial non-sequiturs (see section 4.2.1). The patterns in recommendation throughout the case study seem only loosely to correlate with the actual *content* of the content being recommended.

But some correlation begins to appear, taking a wider perspective by considering genre and its associated formal features such as titling practices. While the actual topic of Bobby's documentaries varied hugely, they were also group-able by a broad topic, as identified (see section 4.3.2). Charlie's adjacent recommendations *Top 40 Popular Songs in 2023* (C80) and *KINGDOM LIVE from LA* - *Maverick City Music & Kirk Franklin* (C81) are distant in terms of their content. But from a formal perspective, both videos are a compilation of songs of roughly the same runtime, and therefore not so different. Similarly, Charlie's recommendations autoplay back and forth from football commentary to games commentary and back to football commentary. From a user's perspective, this represents a strange shift in recommended content, but consider that both modes of content share formal qualities. Both involve commentators talking over gameplay, with long series of videos on the same game.

Bishop finds that media that "go against algorithmically recognized genres [...] are actively punished by the platform," with less exposure, both explaining why the videos on the platform fit into such categories and why videos in those categories are particularly recommended to users.¹¹⁹ Media conforming to algorithmic genres is more likely to be recommended to users, and the fact that it is more likely to be recommended to users means that more media is published that fits into that algorithmic genre. For clarity, I note that these "algorithmically recognised genres" are not entirely genres in the sense that viewer's might use the term, as they are organised on the basis of the features of videos to which the algorithm is sensitive, rather than those to which viewers are. Given that information about what features the algorithm is sensitive to is precisely the black box problem this thesis is concerned with working around, there is no way of definitively knowing what these algorithmic genres are.

However, patterns can be discerned in the output of recommendations that might indicate what these algorithmic genres entail. For example, the algorithm does clearly recognise differences in content, to some limited degree. This isn't to suggest that the algorithm is engaging in direct media analysis, although YouTube does use content analysis for its newest features, so it shouldn't be discounted out of hand.¹²⁰ Instead, I argue that the recommendation algorithm has a number of proxy factors, such as video tags, titles, and the results of collaborative filtering, which together sum to an indication of a given video's content. For one example of this process, between videos C71-77 Charlie's recommendations shuffled through different YouTube channels all uploading video-playlists of pop and rock music in a shared genre. In this case, the algorithm has successfully recommended a series of videos containing the same kind of content, the same genre of music, even though the videos are not all from the same channel. While it is not impossible that the algorithm has detected the genre of music shared by these six videos by 'listening' to it, a simpler explanation would be that it has made connections between the content by their similar titles, the shared artist names in each video's description, and the behaviour of previous viewers of the views. This is the mechanism which declares that users who like Lionel Richie, Eric Clapton, Rod Stewart Michael Bolton (C74) tend also to like Eric Clapton, Michael Bolton, Lionel Richie (C75).

It is impossible to figure out how the recommendation algorithm organises its media genres, and thus the patterns by which it recommends media, from the first principles of the algorithm's preferred formal features. The logic by which the algorithm makes recommendations is thoroughly sealed in

¹¹⁹ Bishop (2018) p.81.

¹²⁰ Peters, Jay (2023) 'There's no way you'll miss YouTube's like and subscribe buttons now', *The Verge*, https://www.theverge.com/2023/10/17/23920088/youtube-like-subscribe-button-animations.

that black box. But it is possible to identify these patterns and algorithmic genres in the output of recommendations. Therefore, the algorithmic genres and recommendation patterns identified here can be used to reverse-engineering the the black-boxed mechanisms by which the algorithm makes its recommendations. This information will help bridge the epistemic gap, explaining how, exactly, the algorithmic telos of maximised user retention leads to the dangerous outcomes discussed earlier (see section 2.4).

Discussion

5.1 Overview

Despite explicitly political preference priming, the shifts in the political content of YouTube's recommendation system demonstrated by these findings seem dependent on the simulated existing views of hypothetical users in only an abstract sense. The recommendation of conspiracy theory content for Bobby isn't obviously the direct result of a progression of increasingly radical recommendations from the starting point of Daily Mail sports coverage. Rather, the recommendation of radical content is one outcome from what seems to be a pattern of genre-led recommendations that are erratic in nature and span many kinds of content. This finding contrasts with Kaiser and Rauchfleisch's findings that right-wing media audiences are only "one or two clicks" from far-right content.¹²¹ But the sudden and severe change in content observed between recommendations wasn't the result of 'clicks' at all; no user interaction determined the shift other than the pre-programmed preferences for right-wing media. In comparison, Ash's static stream of recommendation, and Charlie's similarly unpredictable series of recommendations show that the influence of oppositional priming does cause divergence in content, but that this divergence is unintuitive to the linear model of recommendation progression described in prior research (see section 2.4).

The observed leaps in topic, theme, tone, and other aspects of content between recommendations, from football commentary to either UFO exposés or evangelical church sermons, suggests strongly that the content of a video is not the driving quality for which it is recommended. There are links between the content of videos throughout these recommendation streams (see section 4.4.3). However, the overall erraticism of the recommendations (see section 4.2.1) indicates the primacy of a pattern of formal qualities shared by these videos, only out of which the patterns in content emerge. To the extent there is a connection between the original political priming of these accounts and the resultant recommendations, I will investigate this connection through analysis of the specific formal qualities that directly link the recommendations, rather than only through analysis of the content itself. These formal features include but are not limited to runtime, title text and description tags, YouTube channel of origin, and most significantly the process of collaborative filtering.

I argue that the cause of the extremification effect on this platform and others observed by prior researchers is not as simple as the direct extrapolation from and exaggeration of a user's preferences. Neither is there a straightforward rightward ratcheting effect as a result of an expressly partisan bias. Instead, both of these observed outcomes supported by earlier literature (see section 2.4) are entangled deeply with the nature of the recommended media itself. I will make the case that the logics of political bias operating in YouTube's recommendation algorithm are more directly the products of a system of categorisation and generalisation of media's formal qualities. These formal qualities, described above, are privileged in accordance with the underlying telos of the system, and the ultimate economic aims of its creation. This process, however, indelibly results in the recommendation of extreme and counterfactual content, less directly, but far more insidiously, than the general understanding suggests.

5.2 Interpretation

5.2.1 Runtime

The rawest expression of the telos of algorithmic recommendation is the programmatically challenging preference for runtime that, even with counter-training, saw the recommendation of videos that grew increasingly longer in runtime. As mentioned in the methodology (see section 3.3.1), when not actively skipping all videos over an hour in length, the recommendations became feature-length in just a couple of iterations, and after that quickly transitioned to 24hr livestreams. Even when controlling for runtime, the preference was strong enough that most recommendations remained

¹²¹ Kaiser and Rauchfleisch (2018).

longer than an hour and had to be skipped, and those that were shorter than an hour were consistently only slightly shorter. Even Ash, whose recommendation stream kept playing the same genres of videos from the same channel, pushed and kept pushing for longer videos, even as I enforced a preference against them.

Ash's recommendation stream especially, then, suggests that, uninterrupted, the algorithm would recommend longer and longer videos of the same content, which directly evidences my assertion of user watch-time as the driving force telos of the YouTube recommendation algorithm. Maximising the hours of content consumed also directly benefits the higher telos of the corporate profit-motive, which is underlined by YouTube increasing their control over, and the amount of advertisements on, the platform even further. As of an update in September 2023, YouTube announced it would be "removing individual ad controls for pre-roll, post-roll, skippable, and non-skippable ads" from creators, taking away their power to decide ad placements.¹²² And this comes while the platform is also "cracking down on the use of ad blockers,"¹²³ and "experimenting with [a] heavier ad load,"¹²⁴ redistributing control over advertisements on the platform away from users and to algorithmically decided placements. This process of data systems taking increasing levels of control is what Zuboff calls the 'incursion' of algorithmic power (see section 2.3).

The preference for recommending Ash videos of the same kind of content with longer runtimes is a practical demonstration of the algorithm's telos. A simple user proxy with no preferences and no interaction with recommendation to media will be auto-played the same content of the same type, with longer runtimes, without deviation. This is the mode of interaction engaged in by YouTube's infant user base, from which Google generates a simple profit through advertising "approved as family-friendly".¹²⁵ The system doesn't attempt to branch out into other genres or experiment with the user's viewing by pushing recommendations outside their established taste, as seen with both Bobby and Charlie. (For discussion on the dangers of insulating users in media bubbles, see section 5.2.3.) The overall takeaway from Ash's recommendations is a clear demonstration of the algorithm's end goal in an ultra-simplified case with no complicating factors. Thereby, Ash provides a teleological context in which I can place the recommendation system's response to more complex users with existing views and political preferences. What I observe in Ash's recommendations is is the telos of retention maximisation described previously. The basic mode of recommendation is to feed the user more of what they already like in order to maximise retention for profit, but the complicating factor of existing user preference requires an algorithm to engage in personalisation, a fundamentally different process to interpersonal recommendation.

5.2.2 Formal features and genre

To understand the significance of 'algorithmic genres', contrast the long strings of very similar recommendations with the abrupt shifts in topic, tone, and type. As seen in the case study, these recommendations patterns lead to an unintuitive discontinuity between videos — an associative chain of logic that doesn't seem logical at all (see section 4.2.1). Regarding this thesis's methodology of media analysis, one potential problem is the possibility of perceiving patterns in algorithmic noise. One might read a meaning into chaos and attribute explanations for the data where no deeper cause exists. The impetus of a recommendation system is to generate patterns, in that the retention

¹²² Team YouTube, Rob (2023) 'Simplifying & Improving Ad Controls' YouTube Help,

https://support.google.com/youtube/thread/233723152/simplifying-improving-ad-controls?hl=en, accessed 14/01/24.

¹²³ O'Flaherty, Kate (2023) 'YouTube's New Ad Blocker Crackdown—What You Need To Know', Forbes,

https://www.forbes.com/sites/kateoflahertyuk/2023/10/18/youtubes-new-ad-blocker-crackdown-what-you-need-to-know/, accessed 14/01/24.

¹²⁴ Welch, Chris (2023) 'YouTube tests disabling videos for people using ad blockers', *The Verge*,

https://www.theverge.com/2023/6/29/23778879/youtube-videos-disabling-ad-blockers-detection, accessed 14/01/23.

¹²⁵ 'Ads in YouTube Kids', *YouTube for Families Help*,

https://support.google.com/youtubekids/answer/6130541?hl=en-GB, accessed 15/01/24.

imperative leads to the recommendation of videos similar to that the user is currently watching, as discussed prior (see section 4.2.2). The anarchic characteristics of these recommendations observed in the case study might best be explained as simply the result of dumb direct association occasionally broken up by random noise.

However, while the recommendation streams of Bobby and Charlie are often chaotic and unpredictable, they do not have the hallmarks of an actually random selection of videos on the platform. Specifically, for reasons explained prior, truly random recommended videos would have far fewer views than the videos in this case study do, whereas purely populist recommendations would have much higher view-counts (see section 4.4.2). On that basis, therefore, even these most randomseeming recommendations are the result of an algorithmic personalisation effort, and can be linked causally to the prior recommendations. Indeed, the proxy-user coded with no existing preferences with which to personalise their recommendations was simultaneously the proxy-user with the steadiest viewing experience. This indicates that unpredictable recommendations are in fact a feature of personalisation, rather than a failure in it. What the unintuitive nature of these recommendations reveals, then, is how incompatible the algorithmic process of personalisation is with our personal conception of it.

All algorithmic recommendations are made on the basis of formal qualities, rather than on the basis of a subjective assessment of the content itself, as subjective qualities are beyond the measurement of machine systems, which are not subjective things (see section 4.4.3). The subjective assessment of content, by which people make their recommendations, requires "nuanced determinations", including the ability to make moral and personal judgements, that recommendation algorithms are "without".¹²⁶ But this principle isn't always obvious. The new TikTok users whose first experiences with the recommendation algorithm are accounted by Siles et al (see section 2.1) personified the personalisation system, explaining high-quality recommendations thus: "The algorithm is getting to know me!"¹²⁷ One participant explains increasingly accurate recommendations as: "The algorithm might have read [...] what I've liked. It [also] read that I didn't like certain content."¹²⁸ These responses characterise algorithmic recommendations in the same language as interpersonal recommendations, as if content were being recommended on the basis of the system's personal judgement. Something similar occurs in the case study:

After watching Sean Carroll on Quantum Spacetime (B28) Bobby was recommended a Q&A with Carroll called *Mindscape* on his personal channel (B29). This stands out as a seemingly intuitive interaction amongst a sea of algorithmic noise. When most of Bobby's recommendations, even just within the documentary genre, jump between topic and tone, factual and misinformation erratically, honing in on a specific science communicator across channels seems natural: *If you liked Carroll's explanation, here's where you can see more of him.* Of course, while it seems like recommendation on the basis of content and an ability to recognise an individual, the far more likely explanation is that by identifying the name in the first video's title the algorithm can make a link to the same name in the channel's title.

The recommendation algorithm's ability to track individuals across the platform paired with its inability to make pertinent nuanced determinations and moral distinctions (see discussion in 5.2.2) is a significant mechanism in what Rebecca Lewis calls "radicalisation pathways".¹²⁹ These routes of video recommendations, like the recommendation streams in my case study, lead from ordinary politics to the dangerous content of the far-right through "collaborative connections between influencers of differing ideologies."¹³⁰ These are connections much like those made around Sean Carroll (as above), linking individuals regardless of context. As Ribeiro et al describe in their audit of extremification online, "even distant personalities can be linked in chains of pairwise co-

¹²⁶ Kaiser and Rauchfleisch (2020a).

¹²⁷ Siles et al (2022) p.10.

¹²⁸ Siles et al (2022) p.11.

¹²⁹ Lewis (2018) p.11.

¹³⁰ Lewis (2018) p.11.

appearances."¹³¹ Personalities need not even share beliefs to become linked to one another in the chain of radicalisation online. In fact, the individuals could have directly oppositional views, yet still be linked, because all who "publicly engage in debates"¹³² can be connected. Lewis specifically cites podcaster Joe Rogan (with 16 million YouTube subscribers¹³³ as of 30/01/24) as the largest of these links between ordinary content and the far right, his guest-based podcast/YouTube show continually linking figures across the web.

Linking back to Bobby's recommendations, Kaiser and Rauchfleisch consider whether conspiracy theory content online, such as that recommended to Bobby throughout the case study, "may be a pathway into the far-right, as conspiracy theories are not political per se and thus potentially blur the line between political and cultural sphere and may attract new users."¹³⁴ And in 2023, shortly after running this thesis's case study, Joe Rogan interviewed James Fox, director of *The Phenomenon* (see section 4.3.1), as a clear example of how new radicalisation pathways form; this new video creates a new link between Bobby's recommendation and far-right content through *The Joe Rogan Experience*. While these connections occasionally seem on the face like humanistic recommendations approximating a genuinely interpersonal understanding of user preferences, the absence personal nuance allows for the recommendation of increasingly extreme and increasingly right-wing content, even when most actual individuals "are not supportive of alt-right, racist ideologies".¹³⁵

But, as Kaiser and Rauchfleisch argue, "without the ability to make nuanced determinations about content, the algorithms sidestep questions about the veracity of the information presented and extremist speech."¹³⁶ An example in my case study exemplifies how genre and formal similarities link together trustworthy and untrustworthy information sources without distinction. When Bobby is recommended, back to back. Captain James Cook: The Incredible true story of the World's Greatest Navigator and Cartographer (B50) and The War of 1812 (B51) it seems to be the continuation of a pattern of generically consistent but topically imprecise recommendation of documentary film. Both are feature-length documentaries on historical subjects, even if the topics of those documentaries are fairly distant from one another. But while the latter documentary is produced by Buffalo Toronto Public Media, a "binational public broadcasting organization," subsidiary of the Public Broadcasting National Public Radio (NPR), and producer of professional education Service (PBS) and programming, the former is from a hobbyist YouTube historian called Heroes and Legends Documentary Channel.¹³⁷ Recommendation guides Bobby from one to the other, suggesting an equity of expertise and equivocating the information implicitly. This is especially important when the ambition of 'Heroes and Legends' is to defend those "condemned unfairly by history," like Cook, Amundsen, Napoleon, and Thatcher.¹³⁸ Not only is the algorithm recommending unverified informational content dressed up like factual work, but because media can only be recommended on the basis of formal qualities, rather than understanding of the content, it associates potential misinformation with professional documentary. The co-recommendation of these videos shows that the system's grouping of algorithmic genres not only includes videos of very different topics, but also of very different levels of reliability. This underscores that the algorithmic telos, the priority of the system, is user retention, meaning watch time for the purposes of ad-revenue, and behavioural prediction for increased future ad-revenue, as per Zuboff's analysis (see section 2.2). The formfocussed grouping of algorithmic genres explain the system's laxity around conspiracy theories and other misinformation. This identified mechanism accounts for the system's capability for extreme

¹³¹ Ribeiro et al (2020) p.131.

¹³² Ribeiro et al (2020) p.131.

¹³³ 'PowerfulJRE' *YouTube*, https://www.youtube.com/channel/UCzQUP1qoWDoEbmsQxvdjxgQ.

¹³⁴ Kaiser and Rauchfleisch (2020b) 'The German Far-right on YouTube: An Analysis of User Overlap and User Comments', *Journal of Broadcasting and Electronic Media*, 64:3, p.392.

¹³⁵ Bryant (2020) p.89.

¹³⁶ Kaiser and Rauchfleisch (2020a).

¹³⁷ Buffalo Toronto Public Media 'About' page, https://www.wned.org/about/.

¹³⁸ 'Heroes and Legends Documentary Channel', on *YouTube*.

https://www.youtube.com/@heroesandlegends/about.

content, but not its penchant. But while obscure in this case study data, this penchant has been demonstrated by prior literature (see section 2.4).

One explanation for extreme content founded in this case study and in existing literature would be that, given the outlandish claims in the videos recommended to Bobby, the outrage and intrigue of misinformation might well incentivise increased user retention (see section 5.2.4). This potential mechanism mirrors Facebook's privileging of 'angry' reactions over 'likes' in the promotion of content, as discussed by Merril and Oremus.¹³⁹ As such, it reinforces the findings that the very problematic qualities of borderline content explain why it is promoted. As Edelson et al found, misinformation generates more engagement. So when engagement is the system's end-goal, and misinformation generates more engagement, the algorithm will promote misinformation, as it is inherently without the capability for nuanced moral or intellectual judgement which could prevent it from doing so.

5.2.3 The filter bubble effect

As introduced earlier (see section 1.1), the "filter bubble" effect, the process of an algorithm "surrounding a user with their own viewpoints," is central to understanding radicalisation online.¹⁴⁰ While the topics of media recommended throughout the case study are erratic, I argue that the recommendations streams of these proxy users show filter-bubbling in real time as personalisation seals each user into a bubble of personalisation. These filter bubbles are not directly partisan-political, but instead divide the proxy users on the basis of other factors, which I show in itself has political outcomes.

One theme of differentiation between Bobby and Charlie is a pattern in the age of the intended audience, especially at the point of divergence from the topic of sports. Bobby is recommended nostalgic war documentaries (e.g. B58: The Wooden Plane That Terrorised The Luftwaffe), presumably originally intended for an older audience, and a glance at the comment sections of these videos confirm that.¹⁴¹ Meanwhile, Charlie is recommended gaming videos (e.g. C7: Gotham Knights | Silent Hill | Modern Warfare2), which in turn would naturally target a younger audience. The pattern of age-associated recommendations holds less firmly for Charlie, however, who is also recommended throwback music compilations (e.g. C71: Lionel Richie, Phil Collins, Air Supply, Bee Gees, Chicago, Rod Stewart - Best Soft Rock 70s,80s,90s) and modern (e.g. C80: Top 40 Popular Songs in 2023) in direct succession, representing a range of eras and assumed audience age. But, reinforcing this analysis, the pattern of age-segregated recommendations reflects in the initial recommendations of football commentary, to Bobby and Charlie. Bobby was auto-played episodes of Off the Ball and Charlie, In Soccer We Trust. The first is a radio show, the second a podcast; traditional media vs new media. This pattern of differentiation in age is not the result of initial programming, given that I did not define Bobby and Charlie with different ages when creating the accounts (see section 3.3.2). The only difference is the media preference training, and the predictions algorithms can make on the basis of that existing preference.

Again, the black box problem makes discovering the exact reason for these apparent assumptions as to the age of the proxy users impossible. But if the output of recommendations suggests a difference in personalisation on the apparent basis of age, this must be a result of the inputs provided at the start of the case study, of which there is only the pre-programmed preferences for different media outlets. Of the major UK newspapers, "The Daily Mail [...] have the lowest percentage of millennial audience make-up, at just 14%," and "the largest percentages of over 65s, making up almost half of their audience," while "The Guardian's audience is fairly evenly split and has the joint-smallest percentage of over-65s in its readership, at 21 percent."¹⁴² Based on the input of preference for these two news channels and the output of recommended media associated with audiences of different age groups, it

¹³⁹ Merril, Oremus (2021).

¹⁴⁰ Bryant (2020) p.88.

¹⁴¹ For one example, a leading comment under B55 reads: "The older generation never demand respect because in there hearts they know what they have done and that is what separates them from the younger people today!" from user *QuantumAI-tt6jx*, and liked by the channel owner.

is clear that the recommendation algorithm has executed some assessments about the two users themselves based on only small knowledge of their own preferences. This does not mean, however, that the black box contains any formal process for approximating the ages of users and making recommendations on that basis. More likely, recommendations correlating with user age are the product of collaborative filtering, which is the process of estimating whether or not a user will like a specific unit of content by cross-referencing with users who otherwise view similar content.

But by recommending to a user media that a similar user engages with, YouTube fosters the creation of communities defined by homogeneity which, according to Kaiser and Rauchfleisch, "lack nuance and, especially in the political context, are more extreme than the general mass media landscape."¹⁴³ I observe two component outcomes of the 'filter bubble' effect of collaborative filtering: First, that grouping users into homogeneous communities is itself a dangerous practice. The lack of external influence or dissenting voices on any community is a dangerous thing, but especially when that community has been formed on the basis of media preferences which, as I have shown, correlate with an individual's identity markers. The ordinary result of an echo chamber (confirming a person's world view and insulating them from outside input) being reorganised along demographic lines encourages closed-mindedness as to the experiences of individuals of different identities. Similarly, Sophie Bishop concludes that "gender segregated genres formulated on YouTube are structured and maintained by algorithmic signals,"144 so it is apparent that through this observed mechanism, YouTube could equally form communities correlated strongly with race, sexuality, nationality. This observed mechanism for generating communities of content based on user identity through its association with media preference is not as simple a phenomenon as the algorithm building far-right communities directly. However, forming communities of content on the inclusion/exclusion of certain identity factors is a segregating pattern of recommendation, which will and does create "white supremacist" communities, as found by Kaiser and Rauchfleisch.¹⁴⁵ And on top of the danger of algorithmically curated racist and far-right communities, Noble describes how the correlations capable of being made by recommendation between user preferences and user identity are themselves inevitably based on prejudicial datasets. She argues a history of prejudice will inevitably be "born out in the kind of data that is collected" such that algorithms influencing behaviour will "predict those practices into the future".¹⁴⁶

As discussed (see section 2.4) Lauren Bryant suggests, as an explanation for the overrecommendation of racist content, that the algorithm "found an unexpected relationship between racism and the right amount of curiosity that prompts a person to continue to watch YouTube videos".¹⁴⁷ I argue that, while such a relationship could exist, the over-promotion of racist content can be more empirically explained by the observed tendency of recommendation algorithms to group users on the basis of demographics and other broad generalisations. The filter-bubble effect explored through this case study is generated through the process of collaborative filtering of one user's preferences against similar users' preferences and thus creates 'in groups' defined by uniformity and shared demographic traits. It should not, therefore, surprise researchers that patterns of recommendation online bias in favour of far-right and especially racist content.

My second observed outcome of the filter bubble effect is that, as a result of being built by the algorithm out of users defined by their shared tastes, the homogeneous communities into which users are grouped into are extraordinary in their in-depth focus. I explore next how this sorting of users into media niches with an extreme emphasis on the importance of the topic around which the community is built is an essential mechanism for understanding the extremification process.

¹⁴² Taylor, Henry (2014). 'How old are you again? UK newspaper age demographics in 4 charts'. *The Media Briefing*. Archived from the original on 10 June 2017 via *The Internet Archive*.

¹⁴³ Kaiser, Jonas and Adrian Rauchfleisch (2020a) How YouTube helps form homogeneous online communities, Brookings, https://www.brookings.edu/articles/how-youtube-helps-form-homogeneous-online-communities/.

¹⁴⁴ Bishop (2018) p.81.

¹⁴⁵ Kaiser and Rauchfleisch (2018).

¹⁴⁶ Noble (2020).

¹⁴⁷ Bryant (2020) p.87.

5.2.4 Extremes and niches

To understand the proliferation and promotion of politically extreme content, and to link it causally back to the recommendation algorithm's driving telos, I will use this data set to observe extremification as a general phenomenon before considering how it applies specifically to political content. More directly evidently than extremist ideology, the findings of this case study show a tendency towards the recommendation of content with an extreme emphasis on the importance of its topic. Across different genres, the patterns in recommendation direct different users towards media, YouTube channels, and communities built around specific niches and self-important topics.

Charlie's first few recommendations are of content with a fairly broad appeal, such as Weird ASOIAF Covers Around The World (C6), which is more or less conventional YouTube light entertainment content of the 'tier list' genre. After Weird ASOLAF Covers, Charlie's recommendations heel-turn into a long string of videos (C9-18) on one channel specifically centred on the video-game franchise Resident Evil. After this, the user is recommended another 8 videos (C18-26) of gaming news commentary detailing developments in the "console war" between hardware brands Playstation and X-box. Casual content is recommended briefly, but niche content is repeatedly and continuously recommended, even when the user has no existing relationship with the topic. The channels publishing these videos, Residence of Evil and Xbox Era respectively, are each dedicated to an extremely specific niche within the broader genre of video game media. Each also signpost this niche in each video title with further reference to the franchise/brand and language implying the oversized importance of the topic: Xbox Fight Back Against CMA | Xbox Game Pass Revenue and RESIDENT EVIL 4: REMAKE | MASSIVE UPDATE. While this exaggeration of a video's importance in its title is a well-established aspect of YouTube's essential grammar — often called 'clickbait' — it also speaks to the dedication these channels have to specific topics impenetrable to those outside the content community.

Contrasting Charlie, Bobby's recommendations don't display the same pattern of narrowing down to the content of a specific channel (see section 4.4.3). However, Bobby's recommendations do develop into a genre-niche, as an early run of sports podcasts give way to a 48-video string (B23-71) of documentaries and documentary-type content that share specific tonal and formal qualities (see previous section, 5.2.3). Ash's recommendation playlist evidences this niche effect most emphatically. Their unchanging recommendation stream shows that when a user is simply consuming videos of one type without indicating broader desires or preferences for other kinds of content, the system is happy to let the user stay in exactly that niche for exactly as long as they like. In fact, Bobby and Charlie's recommendations increasingly resemble Ash's as this niche recommendation pattern develops. Whether it is the minutia of Second World War military equipment, extreme in-depth news forecasts for a remake of an old Resident Evil game, megachurch religious ceremony, or, indeed, football, the algorithm trends towards the impassioned and in-depth niche. Instead of a preference for media with broad appeal, as one might expect, casting a wide net for new users, the recommendation algorithm pushes content that demands, and therefore encourages, extreme audience investment. Without user interaction, recommendations push towards these niches based on little more than broad generalisations about aspects of the user's identity.

So, to some degree, this phenomenon is the natural result of a recommendation feedback loop, wherein a user is shown more content in the vein of the content previously shown to that user with increasing specificity. One result of this feedback loop looking for increasingly niche content is that recommendations "lead to low quality or low authority content because that's the only content available".¹⁴⁸ This phenomenon is what Golebiewski and boyd call a 'data void', and they warn that they can be "exploited by media manipulators with ideological, economic, or political agendas."¹⁴⁹ But I argue that, in and of itself, this mechanism of driving users towards niche topics with

¹⁴⁸ Golebiewski, Michael and boyd, danah (2019) 'Data Voids: Where missing data can easily be exploited' *Data* and Society, p.5.

¹⁴⁹ Golebiewski and boyd (2019) p.6.

communities of extreme dedication also naturally bends the algorithmic telos towards extreme outcomes. To demonstrate:

As well as *Resident Evil* news and commentary, Charlie was recommended media in the niche of evangelical worship music and sermons. Assessed as media content, these videos purport supreme self-importance in the literal sense: heaven, hell, salvation and damnation. Users who meaningfully engage with this content are assured that it is the most important content there is to be engaged with, which naturally supports the telos of maximising retention. This doesn't seem problematic in and of itself. But, while I'm careful not to equate the two directly, the same principle is true of Bobby's recommendation of UFO conspiracy theories. Viewers of such media, who believe the claims of the videos, are engaging with existential questions of utmost importance, or so the content asserts: Within the opening minute, *The UFO Phenomenon* (B35) claims its narrative is "the biggest story ever". This is the logical extension of the mechanism that sees misinformation recommended more highly than factual reporting, or even that which drives the preponderance of 'clickbait' online: the more important a video seems, the more likely it is to engage a user, the more likely that user is to stay on the platform, the more revenue the platform generates. Of course, most users don't want to be fed misinformation, but that doesn't pose a problem for retention rates as long as users are insulated from the fact that it is misinformation.

Another incentive of the promotion of increasingly niche media is the lack of similar communities offline that could satiate a user invested in this niche content. For example, a real user receiving Bobby's recommendations would likely struggle to engage in real-life conversations about UFOs, and likewise of any fan engaged with *Resident Evil* in such depth as the *Residence of Evil* channel. If the recommendation of these niche topics successfully hooks users — if the videos' claims of importance engage users — there is little opportunity offline to interact with the niche, thus reinforcing YouTube's place in their media habits and increasing their use of the platform. As such, logically, media with the two qualities of self-importance and social taboo are good candidates for recommendation by an algorithm aiming to maximise retention. These identified qualities are both taken to the extreme in the case of politically extreme content; the further out from the centre a political position is, the more urgent those who hold that position believe the politics are, and simultaneously, the more taboo the position is in the wider world. As such, the algorithmic telos of user retention and watch-time maximisation has a strong incentive to recommend politically radical content.

5.3 Implications

5.3.1 The impact on the audience-user

Lauren Bryant describes the outcome of the YouTube algorithm's filter bubble effect as "interfering with peoples' preferences [...] pushing racist and alt-right propaganda to the surface".¹⁵⁰ This outcome is self-evidently harmful in terms of minority users being exposed to hateful and disturbing content, and potentially even more harmful in the ultimate impact on the users who *aren't* repelled by far-right reactionary content, via increasing levels of hate and real violence (see section 2.4). But while I have already discussed the outcomes of dangerous recommendations in depth, I intend to draw out the further implications from my specific findings and suggest that a new perspective on the relationship between recommendation and radicalisation would elucidate from where exactly the problem emerges.

Prior research asserts, and as such the public understands, that social media recommendation algorithms have a radicalising effect. It is similarly established, though less well-known, that algorithms disproportionately promote far-right reactionary political media. And my findings don't contest the factuality of this. However, I argue, the semantic inverse reveals what is actually happening: Reactionary political content is disproportionately of the kind of content that social media

¹⁵⁰ Bryant (2020), p.88.

recommendation algorithms promote. I justify this perspective by highlighting the mechanisms of machine 'thinking' that result in these dangerous outcomes to demonstrate that they result directly from the system's ultimate telos of user retention, rather than as a side-effect or systematic error.

To summarise the mechanisms identified in my analysis: the algorithm has a strong bias towards longer runtimes (see section 5.2.1), which results in the following preferences. The algorithm prefers misinformation, I suggest because it is usually more shocking and therefore engaging than the truth (see section 5.2.2). The algorithm promotes content and communities in exaggerated media niches which emphasise their own self-importance because these are more likely to maintain an audience (see section 5.2.4). Through this, the algorithm creates homogeneous communities that align with users' demographic identities (5.2.3).

To demonstrate how this impacts the user with a radical and reactionary bias, I revisit the far-right conspiracy theory of 'Qanon' (see section 1.1). The conspiracy theory begins with "a long string of leading questions" like riddles and coded messages called a "Q drop".¹⁵¹ This ludological nature makes the conspiracy theory fertile for the creation of niche communities on YouTube centred around explaining and decoding the 'drops'. And the "cryptic and elliptical" complexity of these messages allows for endless interpretation and reinterpretation fuelling further videos. Blatant misinformation in these videos, such as the claim of widespread "harvesting of a supposedly life-extending chemical from the blood of abused children," incentivises its recommendation precisely because it is so shocking. Any viewer convinced that the conspiracy theory is real would therefore be morally obliged to keep watching videos to learn more, and eventually to take action. Finally, because these 'Qanon' videos began amongst the most extreme fans of Donald Trump, the extrapolated homogeneous community created by YouTube is likely to share those demographic factors. I suggest that this insulated community of mostly white users engaged in far-right conspiracy theories would result in the recommendation of other white, far-right communities including those of white supremacists.

Thus, an algorithmic recommender guided by the basic principle of user retention is incentivised to promote that user extreme and far-right content, and Qanon is a prime example. The real world criminal outcomes directly linked to the Qanon conspiracy theory include "threatening politicians, breaking into the residence of the Canadian prime minister, an armed standoff near the Hoover dam, a kidnapping plot and two kidnappings, and at least one murder."¹⁵² These kinds of costs can not be factored into the algorithmic recommendation calculations of a system that's ultimate objective is to increase user retention. It is therefore not only the users themselves who are impacted by the recommended dangerous media, but their victims, too.

5.3.2 The impact on creators

In turn, content creators on algorithmically driven platforms such as YouTube are incentivised to fuel the mechanisms I have identified in order to be recommended by the system and reach a wider audience.

Golebiewski and boyd identify "media manipulators [who] want to leverage search engines and search-adjacent recommendation engines to amplify content and get it into the hands of as many searchers as possible, regardless of whether the content is actually what a searcher seeks".¹⁵³ And while this is certainly a factor in radicalisation online, I emphasise that the recommendation system itself incentivises all creators on the platform to engage in 'manipulation', because to use the platform requires using the algorithm. O'Dair and Fry analyse the impact of these algorithms "not on the possible effects upon users […] rather, on the possible effects on music creators,"¹⁵⁴ and draw on Bucher's inversion of the 'panopticon' framework in *If* … *Then*, to examine the potential for artists on Spotify to be systematically "shadow downgraded," as an unannounced outcome of recommendation patterns. The algorithmic nature of visibility upgrades and downgrades means "neither the user, nor

¹⁵¹ All quotes in this paragraph from Wong (2020).

¹⁵² Beckett (2020).

¹⁵³ Golebiewski and boyd (2019) p.45.

¹⁵⁴ O'Dair & Fry (2020) p.65.

the artist, will ever be aware [and] due to the use of machine learning, even a human engineer may not be aware of such changes."¹⁵⁵ With no clear information on the logic of the black-boxed system that drives success online, creators are led to follow broad patterns in adherence to the algorithmic telos. Algorithmic preferences incentivise creators to make content with specific features that drive engagement. And via the privileging of nicheness and radical self-importance, creators are incentivised to make content that is more niche and more radically self-important.

A medium's greater economic logic influencing the media itself is not original to social media. For one example, O'Dair and Fry talk about the impact of record labels and radio platforms on artists' content. But the extent to which creatives are boxed into their niche is exaggerated in the age of algorithmic recommendation. Compare, from my case study, *Off the Ball* with *Residence of Evil*. The former is an old-media (radio) show that primarily discusses football, though it also regularly touches on other sports; the latter has a much tighter focus for the smaller niche of a single video game franchise. And yet, on YouTube, at least, the former attracts substantially fewer views that of the latter. *Off the Ball*'s YouTube audience ranges between 3.6K-8.2K views, where *Residence of Evil*'s videos pull in anything between 37K-116K. Almost every video on the channel goes as far as to lead the video's title with "RESIDENT EVIL" in upper-case, and the most recent upload to deviate from the channel's ultra-specific niche severely underperformed (relatively speaking), with only 17K views as of March 2023.¹⁵⁶ And even this video was about a different horror-survival zombie game, demonstrating just how tightly constrictive the boundaries of algorithmically recognised genres can be.

That recommendation seems to push creators into niches reinforces Bishop's work on how proliferation on YouTube is dependant on creators engaging in "self-optimization" towards "complicity with YouTube's enigmatic algorithmic signals."¹⁵⁷ In practice, the observations in this thesis suggest, complicity here involves making content niche and highly engaging, which I argue means content with a high sense of self importance and urgency, regardless of factuality. The potential for this to become a serious feedback loop is self evident. As shown above, the system incentivises creators to extremify their content to receive more views, which means users watching the same channel are now seeing more extreme content. And when recommending those users more content, the algorithm is incentivised to recommend more extreme and more urgent content. This more extreme content is itself incentivised to become more extreme and more urgent to get recommended to more users. As such, the enforcement of certain algorithmic genres, through quiet incentives and dis-incentives, acts on individual users as well as on creators and their content. But the ultimate result of these influences is the impact on the media ecosystem overall.

5.3.3 The impact on the ecosystem

The impact of recommendation biases on creators rolls into changing the media ecosystem online more broadly. Bishop's findings that female creators are being boxed into highly gendered content in specific niches which maximise expected user-engagement, results in a highly gendered media landscape.¹⁵⁸ The consequences of system-enforced high levels of gender segregation in a social media ecosystem can be clearly seen in the example of the incel (involuntarily celibate) niche. This is a group cordoned off into a homogeneous community by their identifying features (young, mostly white, socially isolated men) and who share self-selecting narratives of their own worthlessness, cultivating violent misogyny. Here, the depth and taboo of the 'incel' niche works towards the algorithmic telos because members of the group tell one another there is no hope of a better life outside of their unhappy internet community. As an example, 'incel' community members talk about taking the "blackpill," and taking up to the realisation that "no amount of self-improvement will be

¹⁵⁵ O'Dair & Fry (2020) p.74.

¹⁵⁶ "This Co-Op Horror Game is actually FREE," on *YouTube*, uploaded by Residence of Evil, https://www.youtube.com/watch?v=5XY_IRN7FKA.

¹⁵⁷ Bishop (2018) p.81, p.73.

¹⁵⁸ Bishop (2018).

sufficient to help" them.¹⁵⁹ All these features make the community successful according to an algorithmic telos of user retention; the misogynistic and self-hating ideology of the group tells its members that it is never worth logging off.

This is the kind of community that the rules of interaction on algorithmically driven platforms select for. Not by recommending reactionary content to every user outright, but through a process of media extremification over time. The recommendation algorithm is actively, and often successfully, building a user-base precisely around the traits that make for dangerous outcomes. And as well as incentivising these kinds of communities through filter-bubbling, media recommendation algorithms also have the ability to influence users views. This is what Zuboff highlights as "behavior modification," where the ability of media to influence users is deployed not to personalise content to people, but personalise (see section 5.3.1) and in extreme cases the incentives toward extreme content have created extreme communities of extreme users. But algorithmic telos that results in these outcomes drives every recommendation on the platform. I argue, in fact, that it drives every recommendation across all algorithmically driven platforms.

I argue, therefore, that it is too limiting to think about the dangerous outcomes of recommendation algorithms in terms of enabling already dangerous communities. While that is a concern, I suggest that a much greater one is the way in which these same principles apply across platforms, to all communities. The mechanisms I have highlighted, by which the telos of user retention means the prioritisation of misinformation, isolating niches, extreme views, and homogeneity, apply to the whole ecosystem online. So while social media companies work to stop radicalisation by banning extreme accounts and limiting extreme content, these workarounds don't address the problem's cause. The driving principle of algorithmic recommendation — the gravity of digital space — pulls users towards dangerous ideologies.

5.4 Limitations

My case study is focused on specifically observing the reaction of the recommendation algorithm in a simplified context, so as to draw conclusions from patterns in the data about the system's underlying logics. In limiting the tastes of my users to an extremely simple bit of virtual training, I was able to focus on specific cause-and-effect that training had on recommendations; by limiting the input to the black box and observing the output, I was able to more accurately assess the mechanisms that bridged cause and effect. These accounts are reductive sockpuppets, not more than abstractly representative of a real user, and with a much less complex existing preferences. Even a brand new YouTube user will likely already have data stored on them, given the amount of inter-platform tracking on the web. Conversely, as well as being new to YouTube, my proxy users are built on fresh email accounts never used for anything else. While useful for my specific purposes, one limitation of the case study is that my proxies are not accurate to the scale of data that exists for any real user.

Similarly, the method by which these accounts interacted with media, and so the recommendation system, is much simpler than how actual users interact with the algorithm in their day-to-day use. While autoplay is the default setting on YouTube, and definitely, therefore, the intended mode, it is not the ordinary one. And even those users who do regularly rely on the autoplay function are unlikely to use it in the context of these three users; sitting in front of the screen for hours on end with no input other than skipping videos that were too long. Most users' interactions with any social media recommendation algorithm is endless magnitudes more complex — Spotify, for example, records "half a trillion events every day".¹⁶¹

¹⁵⁹ Conti, Allie (2018) 'Learn to Decode the Secret Language of the Incel Subculture' Vice,

https://www.vice.com/en/article/7xmaze/learn-to-decode-the-secret-language-of-the-incel-subculture. ¹⁶⁰ Zuboff (2019) p.709.

¹⁶¹ Söderström, Gustav (2021) 'Introducing New Spotify Mixes: Personalized Playlists Featuring Your Favorite Artists, Genres, and Decades', Spotify Newsroom, 31 March,

An inverse limitation exists also: while the proxy accounts were sanitised of data contamination to the best of my ability, it is unlikely that I was able to prevent any contamination whatsoever. As per the black box problem, it isn't possible to know every method of data collection employed by Google. But there are some likely causes of data contamination. I didn't, for example, mask IP addresses, which is data Google services collect and which influences recommendations. Other such metadata very likely contaminated the three proxy accounts and factors into the decision-making of recommendation algorithm. However, the significance of this contamination is limited in terms of the relative recommendations of the three proxy accounts. Unintentional data such as my IP address all stems from the same source of the computer from which the case study was run, so any impact on recommendations should be uniform across users.

Other factors I did not control include the respective date and time over which I ran each proxy user's recommendation generation session. This is because to keep track of the data, I had to run the tests in sequence, rather than simultaneously. And because each case study ran over a great many hours, this meant running the case study over several days. While running the case studies at different times wouldn't bias the results, I did account for different times of day in my analysis. For example, C62-67 were the last recommendations generated that evening before pausing the case study overnight by pausing on a video and continuing the next day with C68. C62-67 comprise music for meditation and relaxation, and are tonally clearly distinct from C68, *Led Zepplin IV*. I didn't use this tonal jump as evidence of Charlie's erratic recommendations as it is more easily explainable as the result of an algorithmic attention to temporal factors. I would suggest users are generally more likely to listen to calming music in the evening and heavy metal in the day, and that this abrupt shift in recommendation reflects that.

While Bucher's paradigms provided a framework for the investigation of recommendation algorithms, the very notion of understanding the black box by looking for answers outside of it is inherently limited. Not knowing the internal mechanisms of the system means, not knowing the extent of the system's inputs, which means not knowing the extent to which the methodology of this case study was limited by contaminating data. Further, while I have worked around the black box, the ultimate epistemological problem remains in place, and that is that the exact workings of the recommendation algorithm are not possible to know.

5.5 Recommendations

I argue that the recommendations of preceding investigations like Bishop's or Bryant's still stand. The tech industry's employment of recommendation algorithms requires reform toward accountability; there must be regulation on the broadest scale to control the impact and limit further dangerous outcomes of recommendation systems; and, perhaps most importantly, to introduce public transparency and end the opacity of the black box. Access to these privately owned and operated systems for purposes of research is only a small reclamation of digital social power, but an important first step in protecting digital social space, as well as real life, from being irreparably damaged by the dangerous telos of recommendation systems.

But while the black box stands, I would add to these recommendations, based on my own investigation, that analysis of dangerous recommendations should consider media form as well as content. While it is content itself that has the ability to radicalise users, algorithmic recommendation itself is driven by the association of formal factors. And it is the process of personalisation, as I have highlighted throughout, that ultimately leads a user from ordinary to unsafe content on platforms like YouTube. This process cannot be understood without consideration of the relationship of formal factors that explain why the telos of user retention results in more extreme and more right-wing recommendations.

https://newsroom.spotify.com/2021-03-31/introducing-new-spotify-mixes-personalized-playlists-featuring-your-favorite-artists-genres-and-decades/.

The same inability of the algorithm to recognise extreme content, which leads to its recommendation, plagues the platform's moderation attempts. YouTube have attempted to moderate algorithmically, by "shadow downgrading" videos on the basis of formal qualities such as the wording of a title, video description, or subtitles. But demoting of videos based on the wording of their titles means that, by hiding content containing the word "fascism," YouTube is hiding both fascist content itself and commentary about fascism, ironically including commentary on YouTube's ability to moderate fascist content on the platform. Another flaw in this approach is that it is encourages dog-whistle language and use of euphemisms by those legitimately extremist content creators, which obscures their intentions and makes moderation even more difficult. While it is not possible to verify YouTube's claims about how much dangerous and borderline content their algorithmic downgrading prevents, it is clear from the literature this content remains on the platform and continues to be recommended to users (see section 2.4). As such, moderation has been a limited success, even mores when considering the inoffensive media which has been impacted incidentally by moderation attempts. My recommendation is that algorithmically driven media platforms need a more fundamental change.

The preferences of recommendation systems are not creating radicalisation, the preference of recommendation systems is radicalisation. To put it another way, extremification is not just simply a result of recommendation, it's a function of it, used by the algorithm in its pursuit of user retention, deployed by data corporations in their pursuit of profit. Therefore, data corporations cannot repair these outcomes nor control radical content on the platform, without fundamentally reordering the formal telos that drives the system. And that seems unlikely to change in the pursuit of profit under which these recommendation systems were created and continue to operate. As such, regulation is required either to intervene in the radicalisation process directly, such as the EU Digital Services Act, or to otherwise make radicalisation online unprofitable.

I justified my choice of YouTube as an example platform for this study throughout my methodology, but there was another, more thematic, motivation behind the decision. Like any platform, YouTube wants to maintain its audience, to keep users using. And this is a simple proxy for the profit motive that guides its parent corporation's every decision. But, outstandingly, YouTube doesn't straightforwardly run a profit. Rather, YouTube makes its money by allowing Google to sell advertisers access to users most likely to be influenced by their advert. Zuboff quotes a senior software engineer that, such 'behaviour modification' is used to "put you on a path you did not choose." Not only is it clear that YouTube influences its users' behaviour, doing so is the platform's business model. This influence is wielded most obviously through advertising, which guides users to purchase specific products and services. But every interaction with any media imparts some impact on the user, and therefore every recommendation influences a user's behaviour, some amount. And currently the system of recommendation online is oriented towards radicalisation. An extreme user is predictable. A predictable user is profitable. A profitable user is preferable. Until one of these facts changes, the radicalisation pipeline will continue.

Conclusion

The telos of user retention means that recommendation systems like that on YouTube have an economically driven preference for media with formal features that encourage user retention (see section 2.2). This preference cultivates radical political outcomes, such as increasingly extreme content and an overall reactionary right-wing bias (see section 2.4). My thesis has investigated the precise mechanisms by which this telos results in these outcomes, identifying a series of formal features in media recommended by the algorithm which are also associated with a) extreme and b) right-wing reactionary content. I summarise these formal features as follows:

First, the most influential formal quality selected for by the algorithm was that of a video's runtime. Despite all 3 proxy users expressing a continual preference for shorter videos, longer videos were consistently recommended. This is a direct representation of the algorithmic telos of user retention and how the system prioritises retention over users' expressed preferences. This factor isn't directly linked to radicalisation in and of itself, but is the driving force that motivates the following preferences.

Second, I have identified the recommendation of misinformation, and the promotion of unreliable media alongside trustworthy sources. Primarily, I conclude that this is the result of media being grouped into algorithmic genres, in which media with shared formal features are recommended alongside one another despite important differences in terms of accuracy or reliability. I also outline a mechanism by which I suggest that, in accordance with the algorithm's telos, misinformation is a more effective recommendation than accurate media: outrageous claims are more likely to generate engagement from users, and outrageous claims are also more likely to be false. This mechanism contributes to an extremification effect both by sending viewers to content making extreme claims, and simultaneously, naturally, rewarding extreme content with increased views.

Thirdly, I observe an algorithmic preference for media with a niche and deeply invested audience. While the actual content of recommended media shifted erratically from one video to another, the algorithm repeatedly auto-played videos sending users down deeply specific rabbit holes, whatever the topic. I suggest that this niche preference encourages users to spend more time on the platform, as these specific audience niches, such as *Resident Evil* fandom are unlikely to exist in the same depth offline. Further, I identify patterns of topics which pose existential questions and generally suggest their own self-importance, such as UFOlogy, ancient historical mysteries, and evangelical Christianity. Content involving existential questions such as these are also aligned with the algorithmic telos of user retention both because the questions can grab users' attentions, and because they are unresolved or unresolvable, meaning users can spend endless time watching videos on the subject and never get an answer. Political questions are similarly existential, and outright answers are similarly out of reach. And if political extremity is characterised by dissatisfaction with the status quo, then the more politically radical that content is, the more urgent and existential its questions. As such, I suggest this as another mechanism by which the algorithmic telos results in the extremification effect and the promotion of radical political content.

Fourthly, collaborative filtering creates filter bubbles for users, which result in homogeneous communities and content spheres. I identify that by filtering users by their preferences, these algorithmically created communities coincide with other aspects of a user's identity, including demographic factors. These homogeneous communities contribute to the extremification effect in that they are practical echo chambers. I suggest also that they contribute to an overall right-wing reactionary bias in that an algorithm building communities of exclusion by identity factors is itself a reactionary practice. As reaction opposes social progress and integration, I suggest that the algorithm recommending users into communities segregated by identity disproportionately generates reactionary

communities. And by doing so, the algorithm fills a 'data void' and thus reroutes recommendations to reactionary content disproportionately (see section 5.2.4).

These mechanisms provide an insight into the black box and an explanation of how political outcomes of radicalisation and reactionary bias are brought about in the pursuit of the algorithmic telos of retention maximisation for profit. Specifically, these mechanisms demonstrate that the relationship between algorithmic telos and dangerous political outcomes is not circumstantial, but one of causation in line with the system's end goal. The existing view that I challenge is that radicalisation is a biproduct of recommendation, rather than a straightforward result of its aims. It is true that the algorithm recommends reactionary content. But I argue that the more accurate framing is that that reactionary content is the kind of content that the algorithm recommends. Summarising the overall insight of identifying these mechanisms, I conclude that the recommendation algorithm promotes radical and reactionary content because that content is good for engagement.

'Genie out of its bottle' metaphors, Marina Dekavalla writes, "are evoked to frame the internet as uncontrollable and potentially risky".¹⁶² More specifically, these metaphors associate algorithmic social media's inflexible telos to how genies of myth hold a fool to the letter of their wish even as they change their mind. And this is the general conceptualisation of the danger of algorithms as outlined in the literature (see section 2.4). But I argue there's a flaw in the metaphor in that, in the case of recommendation systems and their driving telos, the wish itself is bad.

Algorithmic recommendation is fundamentally static. Yes, recommender systems adjust to user's preferences and personalise platforms to their changing tastes, but the telos that drives recommendation systems is a static thing. As exemplified by Ash's stream of almost identical recommendations, the simple aim of the system is user retention, because the corporation that owns the platform has, itself, a simple aim of a profit each year larger than the last. So, if reactionary politics is defined as an opposition to progress, it's no surprise the static algorithm moves users in this direction. As long as recommendation systems are driven to keep users engaged for as long as is possible, they will recommend the kind of content that radical content is.

¹⁶² Dekavalla, Marina (2022) 'Metaphors of the virtual: how ordinary people frame what the internet is', *Social Semiotics*.

Appendix

Recommendation stream datasheets.



Experiment Data		Video Data				Analysis		Channel Data	
Video No. (excl. skips)	Runtime Skip?	Video Title	Views	Topic	Tone	Content Notable Recommended	Channel Name	Content Focus	Notable Politics
1 1	00:24:51 N	Argentina vs France reaction: Journalists react to sock Martinez antics World Cup Confidential	5.7K	2022 World Cup final.	Casual commentary	Extensive conversation of the Qatari slavery Daily mail: full spring budget	Daily Mail Sport	Sports	Child of right-wing newspaper.
2 2	00:21:20 N	Argentina vs France preview: Will Mbappe reach Messi-level GOAT status? World Cup Confidentit	23K	**		Little to no significant content.	**		
3	01:48:39 Y	WORLD CUP FINAL EDITION Messi's last chance	4.7K			Boy-ish teasing, limitted political content.	Off The Ball	Sports podcasting.	
4	02:32:06 Y	World Cup final preview, Kilbane, live from Qatar	6.4K						
5	02:32:13 Y	Ronan O'Gara Top 2022 snooker moments	4.6K	Snooker					
6	01:07:12 Y	A CRAPPY QUIZ CHRISTMAS BONANZA	8.2K	Comedy sports quiz	Fun and games				
7 3	00:24:12 N	Crappy Quix: 'You're a w**ker'	4.5K	**					
8 4	00:26:21 N	Ugly scenes at OTB Towers	5K						
9 5	00:25:07 N	Crappy Quiz Toughest ever rapid fire	3.6K						
10 6	00:49:37 N	The longest CRAPPY QUIZ ever!	4.4K	**					
11 7	00:41:36 N	Chaos reigns in one of the most controversial quizzes ever!	5.4K	**					
12 8	00:28:01 N	CRAPPY QUIZ Eoin marks his last appearance	5.1K	**					
13 9	00:31:05 N	THE CRA HAPPY QUIZ RETURSN New look, old cast	4.9K	**					
14	02:30:25 Y	All Ireland reactions: Skehill, Limerick, Lawro on Premier	10K	Sports commentary	Commentary				
15	02:33:56 Y	Irish Six Nations defeat Man United with Andy Mitten	9.3K						
16	02:31:47 Y	Ronan O'Gara & Alan Quinlan on Six nations	9K						
17	02:33:55 Y	Liverpool, Arsenal soarin What happened to United?	11K						
18	02:31:11 Y	Kenny Cunningham in the morning?!	7K						
19	01:28:34 Y	La France; c'est magnifique Six nations Round 4 Review	52K			Rugby coverage, limited notable content.	The Good, the Bad and the	e Rugby coverage.	
20	01:12:04 Y	Danny Care - England's Darkest Day	14K				Rugby Pass		
21 10	00:28:25 N	The league is the premier competition'	946 (new vid)				Off The Ball	Sports podcasting.	
22 11	00:14:46 N	When two props are put into a press conference together	42K	Interview	Interview		Rugby Pass	Rugby coverage.	
23	01:40:27 Y	The Phenomenon (2020) FULL MOVIE	2.2M	UFO documentary	Informative	UFO theories and misleading framing.	UNIDENTIFIED	Cryptids, ghosts, UFOs, a	irConspiracism.
24	03:01:00 Y	Crew-6 Mission Approach and Docking	635K	Astronomy documentary		Little to no significant content.	SpaceX	Rocket launches etc.	No notable politics.
25	03:58:55 Y	Origin of the universe and the Solar System	906K				The Universe & Space	Astronomy documentary	(
26 12	00:53:09 N	The Elegant Universe, Part 1: Einstein's Dream (2003)	136K						
27 13	00:58:30 N	Why Does Quantum Entanglement Defy All Logic?	220K	Physics documentary			NOVA PBS Official	Science documentaries.	
28	01:53:46 Y	Sean Carroli on Quantum Spacetime	117K				Natural Philosophers	Interviews on natural ph	
29	03:01:08 Y	Mindscape Ask Me Anything, Sean Carrol March 2023	175K	Science Q&A	Educational		Sean Carroll	Science talks.	
30	01:18:22 Y	THE 2022 OPPENHEIMER LECTURE: THE QUANTUM ORIGINS OF GRAVITY	979K	Physics lecture			UC Berkleley Events	Educational talks.	
31	01:57:53 Y	Mind-Blowing Facts About our Reality [4K]	6.4M	Pop-science video	Edutainment		Spark	Science documentaries.	
32	01:57:21 Y	Harnessing The True Power of Atoms	1.3M						
33	02:16:00 Y	The Most Jaw Dropping Sights In Our Universe	4.5M						
34	02:11:25 Y	The Unsolved Mysteries of Jesus Christ	1.6M	Ancient biblical mysteries doc.			Parable - Religious History	Religious history docum	eAmerican Christian bias.
35	01:18:47 Y	The UFO Phenomenon Full Documentary 2021	9.7M	UFO documentary		Very misleading framing re: UFO conspiracies.	7NEWS Spotlight	Documentaries.	Anti-trans documentaries.
36 14	00:53:27 N	Actic Sinkholes Full Documentary NOVA PBS	7.6M	Arctic Sinkholes	Informative	Environmental protectionism.	NOVA PBS Official	Science documentaries.	No notable politics.
37 15	00:47:01 N	Monster Tower World Record Building Demolition Blowdown	5.1M	Reality TV about demolition	Reality TV		Free Documentary	Documentaries.	Focus on prisons.
38	02:54:54 Y	Shock and Awe: The Story of Electricity Jim Al-Khali	11M	History documentary	Edutainment		Trey M	Theoretical physics.	No notable politics.
39	01:47:14 Y	Einstein's Big Idea	827K				Slimaks Class	Loose focus on science.	
40 15	00:53:44 N	How Leonardo da vinci Changed the World	2.9M				People Who Changed the	wonginal documentaries.	Great Man history.
41	01:52:47 Y	Henry Ford FULL DUCUMENTARY American Experience PBS	SUSK				PBS America	History documentaries.	No notable politics.
42	01:52:40 Y	Thomas Edison FULL DUCUMENTARY American experience PBS	119K						
43 1/	00:43:36 N	Grand Coulee Dam: A Man-Made Marvel (Full Movie)	3.2M				Bureau of Reclaimation	American intrastructure	
44 18	00:49:23 N	World's Most Extreme Kallway Megastructue Free Documentary	3.4M	intrastructure documentary			Free Documentary	Documentaries.	Focus on prisons.
45	01:28:34 Y	Modern Wonders of the World	3./M	Intrastructure documentary			Naked Science	Materia de comentacion	James May?
40	03-27-46 1	On the tensor of an Anzient Circlingting?	1000	Assist bistony documentary			Provertiere Coll Manufactor In	History documentaries.	no notable politics.
47	02:19:20 1	And and Andrew The County for These Leave days Cities	527K	ancient history documentary			Timeline Marid Ulsters D	Eleinin reposting.	Wedness
48	02.29.451	Ancienc wysteries. The search for three degendary closes	0.1M				Timetine - Wond History D	History documentaries.	wanare.
49	03:27:12 Y	Four Great Megacities of The Ancient World Metropolis Timeline	1.4M						
50	01:21:15 1	Captain James Cook. He incredible true story of the World's Greatest Navigator and Cartographe	1.7M	history documentary			nerves and Legends docum	magne wing pointes.	Great Man history.
51	01:53:16 Y	The War of 1812	5.6M	war documentary			Buffalo Toronto Public Me	d Documentaries and new	s No notable politics.
52	02:09:49 Y	Wild West Marathon #1	732K	Cip compliation			Grunge	Educational "tidbits"	
53 19	00:43:55 N	Battle Stations: P38 Lockneed Lightning (War History Documentary)	3.2M	History documentary	Nostaigic	wardime themes in a broadly de-politicised sense.	Military Learning	Documentaries	Warrare.
54	01:51:24 Y	CL: Silent Wings - The American Gilder Pilots of WWII	1.6M	war documentary		Contrast Rall was a lockwalle attack and the orders defends his support of Utility	Extreme Mysteries	Conspiracy documentari	econspiracism.
55	02:53:35 Y	The Man That Confronted A Dictator Gunther Rairs incredible Story Full Documentary	2.7M	History documentary		Gunther Kall was a Luttwatte priot and the video defends his support of Hitler.	Dronescapes	war documentaries.	warrare.
56	01:10:38 Y	Jet Man The Invention of the Jet Engine. Frank Whittle	1.3M			Little to no significant content.			
57	01:18:32 Y	The Pilot Who Hew 487 Different Aircraft & Landed 2,2/1 Times on a Carrier	404K	war documentary					
58	00:46:43 Y	The Wooden Plane That Terrorised The Luttwatte	1.8M				war stones		warrare.
59	01:10:25 Y	Halifax At War: The Story Bombers of World War II Full Documentary	667K				Extreme Mysteries	Conspiracy documentari	econspiracism.
60	02:10:22 Y	How bid Britain build More Airplanes Than Germany in WW2	3.7M				Timeline - World History D	History documentaries.	warrare.
61	02:27:48 Y	8. The Sumerians - Fall of the First Libes	2.3M	Ancient history documentary	speculative		Fall of Crivilisations	Documentary and podca	Ishistory
62	U3:U5:24 Y	13. The Assyrians - Empire of Iron	11M						
63	01:42:18 Y	How Climate Made History Extra Long Episode	998			Extensive conversation on climate change	nazaros ano catastrophes	Conspiracy documentari	enuminatyming control conspiraci
64	01:20:38 Y	Deserts on the Move	488	Nature documentary	informative				
65	01:07:25 Y	Arctic romp (Frankin expedition documentary)	1.3M	History documentary			William Greenwell	No other videos.	No otner videos.
66	01:47:23 Y	Amundsen: Quiet Conqueror of the Polar Regions	143K		Casual/conversation		Heroes and Legends docum	mHistory documentaries.	Great Man history.
67	01:02:35 Y	Benjamin Franklin - Founding Father of a Nation Documentary	719K		Informative		The People Profiles		
68	01:56:56 Y	Lee & Grant - Worthy Adversaries Documentary	685K	American Civil War documentary		Extensive conversation about slavers without engaging with the morality of slave	y		
69	01:03:57 Y	Battle of Saro Island 1942: America's Worst Naval Defeat0	3.6M	WW2 documentary			Montemayor	Military history docume	r/Warfare.
70 20	00:49:28 N	Why Was The Bismarck The Most Feared Ship Of WW2?	1.5M				War Stories		
71 21	00:33:57 N	Swordfish crews recall the first torpedo attack on Bismarck	373K				Armoured Carriers		

Recommendation stream B (Bobby)

Experiment Data		Video Data				Analysis		Channel Dat	ta
Video No. Iberation	Runtime Skip 00:06:54 N	7 Video Title The greatest World Cup final of all time? Football Weekly Podcast Argentina vs Frace Reaction	3K	Topic The World Cup Final	Casual commentary	Content Notable Recommended One vague mention of "shady" dealings in modern football.	Channel Name Guardian Football	Content Focus Football coverage	Notable Politics Child channel of centre-left newspaper
2 2	00:56:48 N	Argentina beat France in battle for the ages 2022 World Cup Final reaction & analysis	9K			No notable content at all. One mention of "controversy"	In Soccer We Trust	Football podcast	No notable politics.
3	02:56:30 Y 03:22:15 Y	Man United 3-1 West Ham Dvestream MANCHESTER UNITED vs NEWCASTLE LIVESTREAM With mark Goldbridge LIVE	56K 75K	Football commentary	Analysis ==		Stretford Paddock The United Stand	Football games	
5	02:56:53Y	MANCHESTER UNITED vs EVERTON LIVE Stream Watchalong with Mark Goldbridge FA CUP is							
7	03:46:03 Y	Gotham Knights Silent Hill Modern Warfare2	29K	Gaming	Garning podcast		BrokenGamezHDR	Gaming let's play	Gaming, no political content.
8	03:58:16 Y 03:59:32 Y	Halo Infinite Campaign ROE Plays RESIDENT EVIL OUTBREAK w/ Leon Kennedy	8K 16K		Longform gameplay		Residence of Evil		
10	03:59:24Y	RESIDENT EVIL OUTBREAK #3	8X					Gaming news.	
11	03:49:53Y 02:48:12Y	RESIDENT EVIL 2 (98) RESIDENT EVIL 4: REMAKE	OSK OK						
13	02:03:31Y	SILENT HILL 2 REMAKE REVEALI?	4X						
15 3	00:15:40 N	RESIDENT EVIL 4: REMAKE 12 MINUTES OF NEW GAMEPLAY	7K	••		Discussion of Resident Evil franchise, little to know other content.			
16 4	00:04:55 N 00:47:21 N	RESIDENT EVIL 4 : REMAKE MASSIVE UPDATE I RESIDENT EVIL 4 : REMAKE MASSIVE UPDATE I I GAMERIAY & Deveninari	EK 7K						
18	02:56:03 Y	Resident Evil 2 - Leon A / Claire B - Door Randomizer 8	4X			** Exceeding Great and Precious Promises	BawkbaVods	Gaming let's play	
19 20	03:54:05 Y 03:57:35 Y	PlayStation Blocking Xbox Game Pass Xbox Fight Back Against CMA Xbox Game Pass Revenue	BOK GK			Console wars' commentary with a clear partisan perspective.	Rand al Thor 19	Gaming news.	Extreme vitriol against Sony/Playstation
21	03:55:58Y	The Xbox Era Podcast LIVE Episode 125	6K	Console wars	Garning podcast		Xbosfra	Gaming podcast.	Less extreme, still partisan.
23	02:18:48Y	The XbosEra Podcast LIVE Episode 126	3K						
24 25	02:27:41 Y 03:10:52 Y	The XboxEra Podcast LIVE Episode 115 The XboxEra Podcast LIVE Episode 106	.7K .4K						
26	01:37:11Y	The XboxEra Podcast LIVE Episode 107	зк						
27 28	03:46:44 Y 03:33:26 Y	HDGWARTS LEGACY Walkthrough Gameplay - Part 8 (ENDING) 4 DEAD SPACE REMAKE (IMPOSSIBLE DIFFICULTY) 5	5X 3X	Hogwarts: Legacy gameplay Dead Space Remake sameplay		Hogwarts Legacy gameplay, no mention of controversies. Gameolay with little to no notable content.	theJOSHfeed	Gaming let's play	No notable politics.
29	03:31:52Y	DEAD SPACE REMAKE (ENDING)	2X	-					
30	03:24:58 T	Elden Ring SPEARS ONLY Walkthrough Gameplay - Part 2	st 3X	* *					
32	03:19:40Y 02:48:15Y	PSVR 2 Hardwar Pros & Cons, Horizon: COTM - Review Discussion 2 PSVR 2 Lawreb Day is Haralli	9K 5X	Hardware review	Discussion		Virtual Strangers	Gaming hardware	
34	02:58:20 Y	Hubris, LONN (Real Time Review)	.3K						
35 6	03:29:20 Y	Weekend winners & losers USMNT news & roster predictions 2	.9K	Football commentary	Casual commentary	coaming awaros. Discussion of sports news and roster updates, with lots of banter and jokes.	In Soccer We Trust	Football podcast	
37	01:26:25 Y	Matchday Live (R8 Leipzig v Man City Champions League Paris Saint-Garmain - Lille CKC XCK-OFF & Match Centre LIVE	79K				Man City PSG - Paris Saint Course	Football games	
39	03:40:21 Y	** - Bayern Munich	40K		**				
40 7	00:10:47 N 01:00:58 Y	Is now the right time to lure in Florarin Balogun ALL IN for Lionel Messi: MS thinking "outside the box" 4	.K.	Football commentary		PoliticsJOE: Economist explains why britain is poor.	Statin Soccer We Trust	Football podcast	
42 8	0.59:03 N	USMNT roster wishist ahead of March CONCACAF Nations League games	.5K						
44 9	00:56:15 N	Good news for the 2026 World Cup hosts, no Sainthood or Marsch, Pilisic to Atleti rumors	.2K	-					
45 10	00:59:09 N 00:53:28 N	How would a Pellegrino Mitarazzo-managed USMNT play? What the Copa America means for USMNT's World Cup 2026 preparations 6	.7K .5K	-			-		
47	03:01:05 Y	UPPER ROOM LAGOS FEBLIARY 2023 EDITION THE OUTPOLIBING LIGHTN 2022	94K 75K	Worship 	Ecstatic worship	Music-centred worship, with prayer and charismatic service.	Dumin Oyekan	Worship	Charismatic Christian worship.
49	03:23:10 Y	A Time With Jesus	8X						
50	03:11:49Y	Tribl Nights in ATL	.774				TRIBL	Sermons	
52	03:57:23Y	MUSICA CRISTIANA 2022 PARA SENTIR LA PRESENCIA DE DIOS	.904	Worship music stream (spanis	hChristian music	e e M/A (Mr in Example)	Exitos Cristianos 2021		··· Workie mais
54	03:27:00Y	Piano De Fondo Relajante Musica Cristiana Instrumental	м	**		Christian worship music.			••
55	03:53:31Y 03:52:09Y	Instrumental Para Orar Muscia Relajante I LDS MUSIC INSTRUMENTAL	54K 70K			Instrumental music.	PIANO PARA ORAR & P Marx Huancas	Instrumental Music	No notable politics.
57	02:19:42 Y	Piano SUD #4	18K						
59 12	00:44:30 N	Piano SUD #3	8x	••		Instrumental classical music.			
60	01:07:10 Y 02:37:38 Y	Plano SUD #1 Hinos SUD - Plano	4X SK						
62 63	03:56:28Y 02:44:37Y	Musica para dormir SUD , HAY UN HOGAR ETERNO Frenia (Bitual & Marktation Music)	9K 3M	· · Maritation music			 Minir's Well		
64	03:15:30 Y	Beyond the Veil Meditation Music	8X						
66	03:24:21 Y	Eliminte Subconscious Negative Energy	.3M				in the second second		
67 68 13	03:08:37 Y 00:42:38 N	Healing Music for Anxiety Disorders, Fears, Eliminates all Types of Negativity in your Environment Led Zeppin IV (Remaster)	27K 03K	Hard rock music.	Non-reliatious music	(NOTE: Wednesday Morning)	ued Zeppin	Rock music	Limited political content.
69	02:15:14Y	Mothership (full Album)	0M			Full rock album.	en Emorran Indiani Aliusi		
71	02:33:34Y	Lionel Richie, Phil Collins, Air Supply, Bee Gees, Chicago, Rod Stewart - Best Soft Rock 70s,80s,90s 1	82K	Rock/pop from 1970s-80s	Pop & rock	Little to none	Music Collection	Music compilation	Political content obscured by collation.
72 73	03:18:40 Y 02:58:46 Y	Eric Clapton, Lionel Richie, Michael Bolton, Bee Gees, Rod Stewart 2 Michael Bolton, Lionel Richie, Eric Clapton 3	85K 4K						
74	03:07:35 Y	Lionel Richie, Eric Clapton, Rod Stewart Michael Bolton	11K						
76	03:34:08 Y	Phil collins, Lionel Richie, Eric Clapton, Rod Stewart	35K						
77	03:31:45 Y 02:58:54 Y	Michael Bolton, Lionel Richie, Air Supply Top 40 Rock Sones of the 90s	3X 5M	1990s pop music			Soft Rock Playlist Redlist - Rock mixes		
79	01:58:06Y	Miley Cyrus, Maroon S, Adele, Taylor Swift	2M	Contemporary pop music			Pop internacional		
81	03:54:06Y	KINGDOM LIVE from LA - Maverick City Music & Kirk Franklin	.9M	Worship service	Joyous celebration	Christian charismatic worship.	TRIBL	Worship	Christian Charismatic worship.
82	03:59:04 Y 03:56:36 Y	Praise and Harmony Medley Marathon 3 The Grave is Emptyl 3	54K				The Acappella Compar	y Music	No notable politics.
84	03:57:52 Y	Praise and Harmony Marathon	02K						
86	03:55:44 Y	Heavenly God Praise and Harmony Marathon	34K						
87 88 14	03:55:54¥ 00:28:33 N	Songs about neuven 2 Way Maker Jesus Image Steffany Gretzinger John Wilds 6	454				Jesus Image		Christian sermons.
89 90	02:45:45 Y 03:27:55 Y	Hilsong Worship Brit Praise Songs Collection 2022 6 Relatious Songs - Best Praise and Worship Songs 2021	-2M			Music compilation.	Sethurya Hauwa'u Praise and Worshin So	Christian music compilatio	en Christian worship.
91	02:22:08 Y	Songs About God Collection	47K						
92 93	02:53:20 Y 01:57:55 Y	Top 100 Morning Worship Songs for Prayers 2021 JESUS, I NEED YOU	07K	Worship music, no service		Worship sermon and music.			
94 15	00:19:07 N	Yeshua Jesus Image Michael Koulianos	OM SBK	**			Jesus Image	Christian sermons.	Christian sermons.
96	03:42:30Y	Touch Him and Be Made Whole	12K						
97 98 16	00:22:42 N	Yeshua (I Exait Thee) – UPROOM & Bethel worship	.3M	••		Spanish language worship.	Child of God	Christian worship music.	Christian music.
99 17 100	00:18:17 N 01:38:40 Y	Yeshua (Spontaneous) Elevate Worship (feat.Julianna Albrecht) Night of Worship Live at Gateway Church	2.7K			Christian worship music.	Elevate Worship Rateway worship		
101	02:32:48 Y	Bethel Encounter Night	63K				Bethel	Christian sermons.	Christian sermons.
102	03:03:17Y	The Glory of Jesus Michael Koulianos Sunday Night Service 3	SM	Worship service		Sermon of faith healing of depression.	Jesus Image		
104 18	00:35:09 N 02:10:05 Y	Worthy is the Lamb - holy Worship Jesus Image Impartation Sunday Night Service	.714 2X						
106	03:35:10 Y	Jesus, Our Covenant	.4M						
105	02:57:43 Y	Fellowship of the Holy Spirit	2M						
109	03:41:10Y 02:23:12Y	Abide Benny Hinn Sunday Night Service to Homecomine The Live Recording	31K				Bethel Music	Christian music.	Christian worship.
111	03:28:45 Y	Night of Worship & Ministry	SM						
112	02:49:50Y	TRUE NIGHTS: LIVE FROM FORWARD CITY CHURCH	44K				TRIBL	Worship	Christian Charismatic worship.
114	01:32:53 Y 01:31:32 Y	Top TRBL Maverick City Worship Compilation 3 Welt on You	34K				Light of the World Best Playlist of Council	Christian music comolitation	
116	02:38:05 Y	Vision Sunday Sunday Morning Service	5X				Jesus Image	Christian sermons.	
118	02:52:40Y	Sunday Night Service 6	2×						
119	03:45:19 Y 01:48:31 Y	How To Entre In To The Prescence OF The Lord Thurday Moreine Worship	43K						
121	01:33:19Y	25US Full Album Jesus Image	.5M	Worship music, no service					
123 20	00:56:26 N	Michael W. Smith: Surrounded King of Glory, Revelation Song, Way Maker & More Full Concert TBN 1	61K	••		Talk of healing COVID with prayer, but abstracted and non-specific.	TBN		

Recommendation stream C (Charlie)

Glossary: Terms and Definitions

Black Box The obscuring of a process that turns inputs into output, most commonly referring to the specific programming of machine learning algorithms which are unknown even to their engineers. The term is also used metaphorically, including to describe the industrial secrets of data corporations. Media The term media is used throughout to refer to the specific medium of interaction between users and algorithms on different platforms; including music (on Spotify), image (on Instagram), text (on Twitter) and of course video (on YouTube). Content Content refers here literally to media's contents, what is *inside* of it, including topic, tone, moral and political qualities, etc. The qualitatives that one person might use to recommend a work of art to another. Form 'Form' is the term I will be using as the obverse of content; the shadow of the media. Form is the shape of the thing. Form is runtime, viewership numbers, titling, and most importantly and most invisibly of all: the conglomerated histories of every other user that has viewed this particular slice of recommended media, in a process called collaborative filtering. Collaborative A process within recommendation whereby users are cross-referenced with other users sharing characteristics or behaviour patterns and compared in order to filtering extrapolate a preference prediction. **Filter bubble** An isolating outcome of recommender systems "surrounding a user with their own viewpoints, sending their own search terms back at them in the form of results, ensuring that they rarely come into contact with an opposing source."¹⁶³ Reaction Reaction, or reactionary politics is a conservative opposition to social progress, especially characterised online through hostile response to racial, sexual, and gender representation in media.

¹⁶³ Bryant (2020) p.88.

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