Private Platforms, Recommendation Algorithms and Agency: A Study of Tinkerers on YouTube

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Abstract

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The internet and the algorithms designed by private technology companies have become an important sub-field of social science concerned with agency online. The purpose of this research is to examine contemporary online platforms and the predominance of their recommendation algorithms on users to better understand the techniques online users employ to enact agency.

This research develops as a response to apprehension for agency in an online world driven by advertisement-based algorithms, as well as the social problems associated with the sentiment of lack of agency that emerges from these models. This research aims to examine two questions: First, do platform users have agency online when considering the functions of recommendation algorithms? Second, what role, if any, do recommendation algorithms play in that possible agency?

Questions of agency necessarily raise in importance as communication and information sharing moves to online platforms that use algorithms to classify and effect human action. This research is pertinent because its goal is to create knowledge so that we may better understand and act online.

The methodology is a combination of three stages of data collection; initial documentary research of available information provided to the public by Google and independent sources; documentary and case study research of data generated from YouTube and Google; a judgement sampling method to select YouTube users and a thematic analysis of their experiences. This method considers chosen users as expert informants in cases of controversy that help explain collective existence on the platform.

The findings of this research support previous research critical of the manipulative nature of algorithms. This research also contributes to a nuanced view of agency online by finding that agency does occur within technology-literate collaborative groups of users. Conceptualizing content creators and recommendation algorithms as a network of actors within a social context better explains cases of agency experienced by users. The findings support that greater knowledge of technology allows individuals greater affordances of agency.

The research proves that platform content creators are fertile informants for a study of platforms. The typology of content creators is an expansion of previous tinkerer research that supports the continued pertinence of a tech-knowledgeable user typology in sociology concerned with a lack of agency online.

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Introduction:

A significant amount of social action and communication in the contemporary exists online via the internet. This online communication takes place on websites and applications that are created, hosted and owned by private companies. Online communication requires a knowledge of writing code, the digital languages used to communicate with computers. Most everyday users of the internet do not have this knowledge and so it is necessary for websites and applications to be designed by professionals within private companies for layperson use. To accommodate communication, these companies organize and moderate information so that it can be easily found and efficiently used by anyone with an internet connection. This involves creating categories of related information, choosing what is most important, making links between similar information and sifting out anything unrelated or unnecessary. Due to the vast amounts of information being created online, humans are no longer up to the task of organization. Contemporary companies have found another solution, algorithms, sets of rules designed by programmers and executed by computers to organize information.

The larger of these private companies are more often referred to in the contemporary as private platforms or “big tech” platforms. These are the heavy hitters of the contemporary online space, Apple, Google, Twitter, Meta and Microsoft; corporations responsible for organizing mammoth amounts of information (data) on the internet. These platforms create profit by designing products and interfaces that organize data, and they organize this data using algorithms.

The role that these platforms play in contemporary society as private corporations and spaces for public discourse is widely debated because the effects of their information organization has been felt in negative ways. A brief list includes data leaks of personal information, spreading of misinformation, promotion of divisive content, manipulation of audiences, manipulation of the market and influencing democratic elections. The size of contemporary platforms, the massive quantities of data that their algorithms organize and the market incentives that influence how they choose to organize information have become crucial questions for societies continuing to move more communication online.

One of primary concerns of internet users is the amount of control that they have when they are online. Politicians, entertainers and everyday users are concerned about the amount of agency they have online because so much of the space is designed and dictated by platforms and private interests. What has emerged from contemporary social research on these topics is a sub-concentration on the role of algorithms; how algorithms are designed, what types of information they are designed to exclude and how they are trained to manipulate human actions online. The operations of these digital objects designed by private platforms, endlessly executing operations across the internet to organize information and mediate communication, pose very serious questions to sociologists. In the case of this research, the question posed is: To what extent do users of platforms have agency, and what role do algorithms play in that agency?

This thesis primary deals with theoretical problems of agency online and social problems associated with the user sentiment of lacking agency online. Specifically, the theoretical problems of how power is exercised on contemporary online platforms, what counts as agency online, and theories of agency that recognize networks of agents as complimentary to theories that are more concerned with structural criticism.

Specifically, this research challenges the capacity of the theory of “post-hegemonic” power to explain the agency of YouTube content creators and users. Although the theory of “post-hegemonic” power proves to be relevant to YouTube content creators’ and users’ experience, complimentary theories of user agency are also relevant to the experiences of individuals and groups in the study. These are theories that account for the local agency being experienced by users that are part of a larger network of actors.

This thesis addresses social problems associated with feelings of loss of agency online that appear when contemporary technology company algorithms work to guide and limit users. While considering these cases of proxy agency, it is impossible to not also address the social problems of the capitalist market structures that incentivize contemporary technology companies to seek proxy agency.

To examine these problems of online agency and capitalist market structures, this research studies the content creators of YouTube as valuable informants with indispensable knowledge of YouTube, Google and recommendation algorithms. YouTube content creators are people on the ground, contemporary freelancers relying on platforms and recommendation algorithms for their livelihood. YouTube content creators are in a unique position to reveal the operations of YouTube recommendation algorithms and the goals and incentives of YouTube through an analysis of their own lived experiences with the platform as well as with co-creators on the platform.

YouTube content creators' lived experiences cannot be totally explained by theories of agency based in the concept of "post-hegemonic" power. Instead, this thesis states that theories of online agency must be built upon to include the evidence of agency found in the study. Such a theory considers the cases of agency experienced by individuals and groups of content creators and tinkerers on the platform, sprawling networks of agents influencing one another, rather than a reductive conception of unidirectional influences of power.

The types of power exercised by online platforms like YouTube through their recommendation algorithms is specifically pertinent to sociological study due to the ubiquitous nature of online communication and data creation. Algorithms have been charged with functioning to mediate massive amounts of data, meaning that algorithmic technology is everywhere in the contemporary. Previous research in sociology, as well as psychology and marketing, demonstrates the influence of algorithms on human action and possible action, as well as the misaligned economic motivations that lead large companies to make these algorithms. It appears that user motives and platform motives are critically misaligned; users attempt to connect and share, in doing so creating profit and community. Platforms attempt to manipulate and guide, in doing so creating profit and profit-creating communities. Platforms are aware that individuals are more inclined to consume certain types of content, however to create profit, must choose to accept or ignore users' explicit requests. It is shown that this motive misalignment sacrifices the mental health, wellbeing, and the assumption of free choice of the user base.

The sociological research of platforms and their recommendation algorithms creates knowledge of algorithms functions, platform architecture and ultimately how online communication can afford agency. This research is pertinent because its goal is to create knowledge so that we may better understand and act online. The stakes of such research fall in a familiar territory for the social sciences critical of institutions. Specifically, that capitalist market forces lead to private institutions taking advantage of the individuals that rely upon their service. What is novel in the case of online platforms is the consequential stakes of machine learning, artificial intelligence, and algorithms. We must be critically examining the actions of platforms (institutions) as well as the functions of the machine learning algorithms (objects) that they create in an attempt to manipulate behaviour for profit. This type of research widens the lens of critique to consider the algorithms created by platforms as political objects, reflections of their creators and their creators' society. When considering the amount of social action mediated by algorithms, it is pertinent to consider these objects as playing a role in contemporary social action.

The findings of this research support previous work that highlights the manipulative nature of algorithms. While doing so, this research contributes to previous work by challenging the reoccurring narrative in the literature of online users being "infantilized" by "all-powerful" platforms. The primary novel contribution of this research to the existing body of sociology concerned with algorithms and online agency is recognition of platform content creators as a fertile population of study and the subsequent creation of a typology of content creators. The typology of content creators is an expansion of previous tinkerer research that attempts to categorize users to better interpret their content as expressions of agency and map a network of actors. The application of the "tinkerer" category to YouTube is novel, and the category could be used to describe active users on other platforms in future research.

The conception of online agency as occurring through of a network of actors is a useful tool for understanding users' relationships to platforms. This conception accounts for the agency that YouTube content creators experience, unlike absolute critical theory approaches to platforms that concentrate on domination. Critical approaches are not "wrong", as this research shows by confirming the findings of critical research and literature. Rather, the concentration of these approaches on structures of power means that they are removed from the daily reality of platform users.

This thesis is both descriptive and prescriptive; based on the findings, this thesis prescribes greater technology education. This prescription could be considered a functionalist approach to the question of online agency: “How can users have greater agency online?”. This thesis does not deny the greater structural and economic problems posed by platforms, the market in which platforms exist, the motivations that market creates or the negative consequences of that market for users and user agency. What this research does attempt to bring is a nuance to the existing body of work concerned with online agency. Therefore, this research prescribes education as a workable and implementable “treatment” for the threats to human agency present in the contemporary free-market online space. A treatment far from a cure.

The thesis presented is that while previous research critical of the possibility for user agency on contemporary platforms is compelling and supportable, in the case of this research on YouTube, conceptualizing content creators and recommendation algorithms as a network of actors within a certain social context better explains cases of agency experienced by users. The following is a summary of the division of this argument into chapters and their contents.

Summary guideline:

The research begins with a brief glossary of terms and a collection of previous definitions of algorithms that explain the origin of computer algorithms from data. This section includes a summary of machine learning algorithms and artificial neural networks, technologies that are abundant in contemporary technology companies. Two final key concepts are introduced before the literature review; a taxonomy of algorithmic decision making, and a summary of black-boxes and how they apply to contemporary technology companies.

The literature review is organized into six parts. First, a review of literature that critiques the view that computer algorithms’ functions can be considered “objective”, specifically how this view ignores the values of the creators of algorithms. Second, a review of critiques of how contemporary technology companies use algorithms organized into two recurring themes; that algorithmic functions limit human agency on and offline, and that this limiting of human agency if the result of the economic motivations of the contemporary market. Third, a review of multiple authors similar conceptions of a new era of capitalism based on mass-data retention by platforms.

Following this review of literature critical of contemporary technology companies and the market is a review of the first of two useful theoretical frameworks that will be used to structure the findings. The first theoretical framework defines the power being exercised by technology platforms through recommendation algorithms using Lash's conception of "post-hegemonic power". According to Lash, modern hegemony was based in a logic of cultural reproduction, where norms and institutions remained stable through a transparent domination of subjects. People were aware that institutions dominated their social and political existence and consented to that domination because those institutions provided a relatively stable group existence. In contemporary post-hegemony, domination has an invisible character, it exists through communication rather than ouverte rules of institutions. According to Lash, this means that an individual's consent is no longer required for her to be dominated. According to this theory, recommendation algorithms and the contemporary platforms that create those algorithms are responsible for the monitoring, guiding, and directing communication without user content. This post-hegemonic domination through communication causes a loss of user autonomy online.

The second theoretical framework acts as a response to the first framework and it will be argued better applies to the findings of this study. Based on the work of Van Dijck and Gillespie, this theoretical framework recognizes local cases of consent and agency as existing within networks of users that can be considered collaborative communities. These local cases of agency are the result of information sharing and education, framing users as playing a very active role in the creation and functioning of algorithms.

Finally, the section concludes with a review of hobbyist/tinkerer literature, which argues that individual and group agency can be realised through the objects of the environment, in this case, algorithms. This literature provides context for applying the Van Dijck and Gillespie theoretical framework and highlights the importance of collaborative education.

The following section details the research methods of the study; the initial documentary research, the criteria for the selection of themes, a description of the informant selection process and justification of why "controversies" are data-rich points of study. This section concludes with a summary of the initial documentary research findings on the functions of YouTube recommendation algorithms. The two principal findings "Watch-time (a history)" and "machine learning on YouTube" were critical early findings that influence the following results section.

The results section describes the four principal findings of the study; user personalization, user behaviour being influenced by algorithms, "Freshness", and content suppression. First, the reality of "subscription burn" and subscription optimization show that when creating recommendation algorithms, YouTube is concerned with the categorization of users so that recommendation can be personalized to the user based on associations between those created categories. Second, search-engine optimization efforts by content creators, preferencing of implicit metrics by YouTube, and the standardization of content are findings that show user behaviour being influenced by algorithms**.** Third, the mental health crisis experienced by content creators on the site shows an effect of the metric "freshness" as well as demonstrating how YouTube attempts to avoid culpability for algorithmic functions. Fourth, content suppression further reveals YouTube's self-interest, while also providing examples of failures of algorithms. These four findings are associated with the sections of the literature review in the subsequent discussion section.

The discussion section is separated into three parts that follow the themes of the literature review in the order that they were presented. First, a discussion of personal data and behavioural data, and how the findings of this study conform to literature critiquing the manipulative goal of data collection and categorization for economic reasons. Second, a discussion of the effects of recommendation algorithms on content creators and their content, and how these findings conform to the literature as instances of post-hegemonic power. Finally, using Van Dijk and Gillespie's approach, a discussion of the existence of user agency despite recommendation algorithms. This is done through the creation of three categories of explicit users found during the study, "tinkerers/hobbyists", "entertainment/commentary (EC) creators" and "YouTube-affiliated creators”. This concluding discussion presents the findings as evidence of a network of diverse explicit users that make up a collaborative community. The collaborative community is affected by recommendation algorithms and is also influencing those algorithms.

The conclusion endorses previous research prescribing education and technological literacy as a solution to a loss of agency online. Two limitations of the research methodology are identified, and a future direction of research on sub-categories of tinkerers is suggested.

Without first understanding the basic history and operations of algorithms, notions of tinkering and the affordances of agency offered by education are difficult to perceive. The following section introduces algorithms, machine learning technology, black boxes, and contemporary social media platforms.

A brief introduction of terms: What is a recommendation algorithm?

The rules of basic arithmetic oblige an order of operations to correctly solve math problems that involve addition, subtraction, multiplication and division of positive and negative numbers. These rules organize how people wishing to solve a math problem interact with symbols; solving a problem in order of parentheses, exponents, multiplication and division, and finally addition and subtraction (Mathcentre, 2009). While teaching methods of these rules vary, every alternative of the concept remains step-by-step instructions to solve an equation (Taff, 2017). These methods are examples of algorithms; step-by-step methods used to process data (an equation) to produce a desired output (a solution).

> *"[An algorithm is] a finite set of rules which gives a sequence of operations for solving a specific type of problem."*
> (Rogers, 1967, p4)
>
> *"…an algorithm is a clerical (i.e. deterministic, book-keeping), procedure which can be applied to any of a certain class of symbolic inputs and which will eventually yield, for each such input, a corresponding output".*
> (Knuth, 1968, p1)
>
> *"In order to produce a particular output, such as a series of binary digits, the computer must be given a set of explicit instructions that can be followed without making intellectual judgments. Such a program of instructions is an algorithm."*
> (Chaitin, 1975, p48)
>
> *"[An algorithm is] a step-by-step procedure which, starting with an input instance, produces a suitable output. It is described at the level of detail and abstraction best suited to the human audience that must understand it. In contrast, code is an implementation of an algorithm that can be executed by a computer."*
> (Edmonds, 2008, p1)

Computers are responsible for processing incoming data, represented in binary numbers (input), to provide outgoing data (output). Sets of instructions are programmed into computers to process input data and subsequently produce an output. Algorithms are the step-by-step instructions followed by a computing agent to "complete mechanical manipulations of numbers" without requiring any understanding of the results of any individual step (Chaitin, 1975, p48).

Computer algorithms are defined by four shared core features; finiteness, definiteness, input, and output (Rogers, 1967, p5-7; Knuth, 1968, p1-2). First, algorithms must have a finite number of steps and must terminate. Second, the instructions and language of the algorithm must be unambiguous. Third, incoming information is necessary for an algorithm to begin providing step-by-step instructions to a computing agent. This includes the absence of input, because an input of zero may be the quantity required for an algorithm to initiate further steps. Finally, due to their finite nature, algorithms must provide outgoing information related to the incoming information.

Less agreed upon alternate qualities of algorithms have been suggested. According to Rogers (1967), an algorithm should have a reasonable number of steps. An "optimal" algorithm determines an output using the least steps possible, which appears to be an aesthetic preference that occurs often in computing, similar to an Occam's razor approach (Rogers, 1967, p7). Knuth also includes that faculties to store and retrace steps are a necessary feature of algorithms, although this is no longer the case in the contemporary (Knuth, 1968, p1-2).

Data was originally seen as a by-product of computer usage that must be stored; now it is seen as a resource that can be used (Alpaydin, 2016, p11). Individuals involved in technology assume that there must be common underlying motivations that drive people to use computers. They believe that those motivations may be identified by finding patterns in data and therefore make predictions about peoples future behaviour (Alpaydin, 2016, p13). The process of attempting to recognize patterns in data to approximate motivations of computer users is called "data-mining".

In the contemporary, due to the sheer quantity of data available to programmers, any effort to manually program algorithms to recognize patterns and data-mine is time consuming, costly and largely ineffective (Alpaydin, 2016, p23, 50). "Machine learning" emerged as a subfield of software engineering to try and transfer the heavy workload of humans onto faster functioning algorithms. Machine learning refers to machines that can automatically produce algorithms based on large amounts of existing data that function effectively when faced with new data (Alpaydin, 2016, p39). Generally, it is an attempt by programmers to create machines that can autonomously classify their own functions as effective on ineffective when processing new data, and automatically alter their functioning to produce a desired output; a machine that can *learn* rather than just be *taught*.

Two main types of machine learning exist, supervised learning and unsupervised learning. In supervised learning, the desired outputs of an algorithm are defined by programmers. Algorithms are then trained to auto-adjust their functions to produce an output as close as possible to the provided output (Alpaydin, 2016, p110). For example, text analysis algorithms may be programmed by a human to detect certain words that the programmer considers discriminatory or rude, and when these words are detected in a YouTube video title, algorithms function to either supress or erase the video (Alpaydin, 2016, p70).

In unsupervised learning, no desired outputs are defined by programmers, rather algorithms function to identify patterns in large data sets. For example, algorithms tasked with analysing demographic information and video consumption data of users may identify clusters of video consumption related to the age and location of viewers and a certain content creator (Alpaydin, 2016, p111). This type of work has been previously done by humans with expertise in statistical methods. However, due to the sheer quantity of data now available, unsupervised learning algorithms are considered more adapt at identifying trends than humans (Alpaydin, 2016, p115).

Different versions of these machine learning algorithms are meshed together by programmers into complex networks of algorithms, commonly known as deep learning networks or artificial neural networks. Artificial neural networks are layers of algorithms that are governed by learning algorithms designed to imitate neural networks of the human brain (Alpaydin, 2016, p85). Multiple algorithms are organized into layers programmed to transfer data to other layers. Each layer is responsible for making abstractions of very fine input data that is then used as input data by the following layer of algorithms (Alpaydin, 2016, p89). The following layer is programmed to process the new input into a greater abstraction of the original data. The process continues through multiple layers, until the abstracted data is processed by the final layer of the network, which is responsible for computing the final output. This final output is a much more detailed and complex abstraction of the original data, that has moved though many layers of the network and been made much more nuanced. In the example of facial recognition neural networks, this allows individual pixels of an image (input layer) to be recognized as a composite image complete with patterns of colours, lines, and edges (middle layers), and to be finally recognized as a photo of a cat (output layer).

While some commentators in the field of machine learning discuss the possibility of creating deep neural networks of machine learning algorithms that achieve consciousness, what is more pertinent to contemporary technology companies is creating machine learning algorithms that most effectively predict and influence human action. This goal is of specific interest to the designers of social media network algorithms, which are the target of this research (Meta, Twitter, Google, etc.).

Social media algorithms:

In the case of social media networks, algorithms are "a programmable architecture designed to organize interactions between users" (Van Dijck, Poell, de Waal, 2018, p9). These algorithms are designed to compute outputs from various inputs and often function as decision-making tools. To compute an output, an algorithm computes how closely a certain input resembles the classifications provided by training data, in turn executing a pre-determined function. Diakopoulos creates a useful four class taxonomy of algorithmic decision-making when producing outputs; prioritization, classification, association and filtering (Diakopoulos, 2014).

Prioritization is the emphasis of certain inputs that are deemed especially relevant, allowing for more efficient triage of large amounts of data (Diakopoulos, 2014, p400). For example, airport screenings prioritize disabled passengers or may deliberately screen passengers they have defined as "high-risk". Classification is the organization of inputs as belonging to distinct classes based on certain features of the entity (Diakopoulos, 2014, p401). Similar to biological classifications of genus or book genres in a store, an algorithm classifies inputs to better organize large amounts of data. Association is the identification of relationships or similarities between certain inputs based on the particular qualities they have been classified as possessing (Diakopoulos, 2014, p402). For instance, an algorithm on Amazon may recommend a user the types of books or music associated to the user's previous purchasing habits. Finally, filtering is the inclusion or exclusion of certain outputs depending on how it is judged to be relevant

(Diakopoulos, 2014, p402). An algorithm may filter certain videos that are deemed to contain content inappropriate for children similar to how a copy editor may improve the readability of a news article by filtering repetitive language.

Diakopoulos' taxonomy of decision-making is useful to understanding the types of procedures that algorithms most commonly dictate in computing. However, these decision-making functions are by no means separate or distinct. Recommendation algorithms execute all functions to arrive at a certain output. For example, to properly *prioritize* certain content and *filter* irrelevant content, algorithms must *classify* input and make *associations* based on those classifications. Algorithmic processes are therefore complex webs of computations using multiple functions simultaneously.

The process of prioritization, classification, association and filtering is a process of categorization and discrimination of input (Dormehl, 2014, p6). The categories used in establishing algorithms to generate output are in constant flux, changing due to machine learning, user actions, software designers' desires, advertising desires, world events, audience reactions, markets, and the interests of platform executives. Algorithms' outputs are therefore the combination of manifold assessments and categorizations of inputs; what appears to be a simple output is produced through multiple decisions by multiple actors.

The fluidity of these decision-making functions reflects the fluidity of the many actors that co-produce the categories to produce an output. For example, an algorithmic recommendation on a social media network. Consider that you, the reader, log into an online shopping website using your account. Arriving on your personalised homepage, you may access a history of your previous purchases, change billing details, cancel subscriptions, or search for new products. Interestingly, the majority of personalized homepages on online shopping websites present you with items available for instant purchase that may interest you. You notice an e-book with an interesting title. Hovering over the e-book's summary reveals that the novel was written by the same author of a film adaptation that you recently purchased on the site. The e-book has been reviewed by 42 reviewers, and 19 of the reviewers have similar tastes to your own. These items are selected and presented to you using algorithms whose input is your previous purchases and activity on the website related to other user activity. The algorithms producing this output are known as recommendation algorithms.

Unlike mathematics, where there is one set of universal rules, the algorithms of social media networks do not have any *one* objective "formula" for recommendation. The diversity of the processes of recommendation are rendered invisible to the social media user for multiple reasons, an obfuscation process often referred to as a "black box".

Black boxes

Recommendation algorithms are responsible for guiding users' actions online (Pasquale, 2015, p59). Software engineers design algorithms to organize and guide online interaction between users and conceal the step-by-step procedures of their algorithms within "black boxes". A black box is a technology or device that has observable inputs and outputs but mysterious or hidden inner functions (Pasquale, 2015, p3). While black boxes are considered arbitrary in some situations, like open-source online video game projects, they become more important for companies that collect users' personal information. Advertisement-based platforms like YouTube, Meta and Twitter aim especially at analysing and selling audiences to advertisers. This is most effective when audiences are unaware of the categorization process (prioritization, classification, association and filtering) and thus behave uninhibited online (Pasquale, 2015, p66). If a user understood the contents of a black box, the user could "work around" algorithms.

Workarounds are practices that overcome a perceived limitation or problem in an existing formal system to achieve a different outcome that is considered more desirable (Alter, 2014, p1044). For instance, when activists accused Twitter of censoring hashtags related to WikiLeaks and occupy movements in 2011, Twitter revealed black boxed techniques about how trending algorithms identify and filter content, leading to users gaming the algorithms to promote their own content (Pasquale, 2015, p77). This is an example of Twitter users working around some perceived limitations of the platform to promote their own content and increase their online reach more effectively.

Black boxed algorithms provide a marketing advantage for companies seeking to make profit. For example, companies claim that they cannot be transparent due to the risk of revealing trade secrets to competition (Pasquale, 2015, p81). Revealing the metrics and weights recommendation algorithms preference provides rivals a competitive edge, the knowledge of how to offer similar or better services to advertisers. If a publishing house had knowledge of the techniques Amazon uses to recommend media to prospective Amazon customers, the publishing house could game Amazon's recommendation algorithm to promote their own publications. This activity undermines Amazon's recommendation goals and may threaten profits by recommending certain media to users that Amazon believes those users will not be interested in consuming.

Platform providers therefore create barriers between their algorithms and interested parties to uphold their own interests. These include technical barriers between users and algorithm techniques, legal intellectual-property barriers between software engineers and the right to divulge algorithm techniques, and deliberately complex administrative and technological barriers to obfuscate techniques in publicly available information (Pasquale, 2015, p6). Platform providers claim that these methods are necessary due to the risk of users, advertisers and competitors taking advantage of their systems (Pasquale, 2015, p65). According to the algorithms' creators, to reveal the inner workings of a black box would be bad for business.

Black boxes are good for business but limit users' understanding of the consequences of their online behaviour (Pasquale, 2015, p66). Pasquale makes the argument that not only are the technical functions of algorithms hidden within black boxes, but so are the values imbued into the algorithm by their creators. Therefore, platforms may also use black boxes to justify refusals to divulge controversial decisions of content privileging or suppression (Pasquale, 2015, p65). Research into algorithms and the functions of black-boxed algorithms, is political work that calls for greater transparency and attempts to understand how power is exercised to advantage one group's interests over another. Cinnamon similarly notes that the asymmetrical accumulation of data favouring platforms over users creates a class relationship where the majority of the commodity of data is held by platforms rather than users. (Cinnamon, 2017, p613).

Diakopoulos (2014) and Pasquale (2015) make compelling arguments for transparency. An increase in transparency of how recommendation algorithms guide user behaviour would result in a better-informed user capable of making conscious consumption decisions online (Diakopoulos, 2014, p403). Transparency would force platform providers to reveal the extent of their role as data brokers and consequently encourage privacy of information and build public trust. However, opening advertising platforms to the possibility of manipulation from users or competition risks business profits.

Observing inputs and outputs may allow researchers to reverse-engineer recommendation algorithms to reveal their processes of prioritization, classification, association and filtering. Diakopoulos suggests collecting information from participants attempting to work around black boxed algorithms to better understand how algorithms function and how power is being exercised by platforms. This type of data collection directly influenced the direction of my research.

To summarize; algorithms are necessary elements of social media networks; Algorithms are subject to intellectual property (patent laws) due to their value in making profits; This makes algorithms, and the inherent value-based decisions incorporated in the algorithms' operations, invisible; Invisible algorithms are an exercise in power, where some people are advantaged and others disadvantaged by the algorithm's operations. Therefore, investigating the limits and affordances of algorithms is important for understanding how power and agency are exercised in society.

Literature Review:

How algorithms are structured and deployed to produce outputs that have economic value has come under scrutiny in the social sciences. In this review of the literature, I present what is known about algorithms as they are used in social media networks and the implications of those uses according to leading researchers and theorists.

First, I review the critique of algorithms as objective. Due to algorithms being objects related to computers they are often considered objective actors or not considered as actors at all. This literature puts forward that algorithms are, in practice, instilled with the values of creators as well as the values of the social environment in which they are designed. As such, the literature argues that they should be considered as value-based actors.

Second, I review the extensive literature that critiques contemporary technology companies and their algorithms on two fronts; first, the guiding nature of social media algorithms as contributing to a loss of human agency; and second, the economic motivations of the contemporary market that encourage technology companies to design manipulative algorithms. This literature generally conceptualizes agency in a rationalist tradition, whereby an informed actor may act freely after rationally considering their interests. The literature is concerned that algorithms function to manipulate rational users and thereby rob them of their agency online.

Third, I review multiple authors' conceptions of a new era of capitalism related to algorithms. Although the different authors' concepts are distinguishable, they all describe a perceived social shift that is related to massive data retention by private corporations.

Following these critiques of algorithms in the literature, I will review a theoretical framework based on the work of Scott Lash and David Beer concerned with Lash's concept of "post-hegemonic" power. The framework appears to apply well to the study of search and recommendation algorithms on social media networks because it theorizes a novel type of coercion via a control over access to communication. Lash stresses that this type of coercion relies on hidden rules, which Beer identifies as existing within contemporary social media platforms and their black boxed algorithms.

In response to the review of Lash and Beer, I review the work of José Van Dijck and Tarlton Gillespie to propose a counter theoretical framework that locates many occasions for user agency on platforms. Both authors are generally concerned with the empowering function of education, Van Dijck doing so by categorizing explicit users as practicing agency, while Gillespie proposes that all users play a critical and possibly even mindful role in recommendation algorithms' functioning.

This theoretical response to critical algorithm literature forms the basis for the closing review of the "hobbyist" literature. I review Wiebe Bijker theory of individual and group agency as being symbolically contingent on the surrounding objects and environment. This facilitates the combination of Van Dijck and Gillespie's work with empirical examples of agency on and offline. This is the research approach used in my study of users and content creators (hobbyists) on the YouTube platform, YouTube recommendation algorithms and the effects on user agency.

False objectivity of "the Algorithm" and algorithms as value-based actors:

The public generally considers that algorithms are objective because their operations are computational and thus devoid of subjective affect or feelings (Bilić, 2018; Gillespie, 2016a; Gillespie, 2016b; Beer, 2013; Kitchen and Dodge, 2011; Gillespie, Boczkowski, Foot, 2014). This position has been extensively critiqued as confusing the computational functions of algorithms as the rational unmotivated actions of machinery.

When faced with a mechanical assembly line, such as a car body assembly line, an individual rarely imparts subjective agency to any functions of a machine. First, small cranes depose dismantled car parts onto a conveyor belt; the parts are transported by conveyor belt to awaiting mechanical arms that are charged with placing the parts under a mechanical press to achieve a desired shape; after a time, the parts are attached to a chassis that awaits on a separate automated platform. Eventually, the machines' output comes before the eye of a human inspector, an individual with the uniquely human role of assessing the machines' mindless or value-neutral work using their own subjective experience. This is an example of machines being viewed as neutral objects, incapable of agency, desire, or motivated action, objects that must be surveyed by humans because they are devoid of affect.

The non-neutrality of objects:

Machinery, as an object, is the product of human creators, and those human creators are the products of the social conditions of their society. In this way, objects are products of their creator society. According to Herbert Marcuse, an object ceases to be neutral when influenced by the power of others, regardless of the objects non-human nature (Marcuse, 1941). Objects such as machinery are being incorrectly perceived as rational, objective, or neutral by society because they are being defined as non-human (Marcuse, 1941; Bilić, 2018, p318).

Marcuse explains the social conditions of the Western post-industrial era as being motivated by "technological rationality" (Marcuse, 1941). Technological rationality was the widespread and accepted desire to increase profits by increasing production or perpetuating scarcity (Marcuse, 1941, p160). Marcuse was particularly concerned with technology and manufacturing techniques (together called *technics*) because they are the products of the desires of a particular society and can therefore be studied to better understand the social conditions and rationality of the creator society. Technological rationality is embodied in the technics used in industrialized societies and all technics is instilled with the goal to increase profits.

In technologically rational societies, technics replaces external authority to coerce and dominate the individual through individualized values of self-discipline and self-control (Marcuse, 1941, p148). For Marcuse, when an individual properly uses technics, the individual is in fact being coerced by the creators of the technics and their desire to increase profit. If profit increases, then the technics is deemed to be properly functioning, and the socially constructed nature of technological rationality is being hidden from the individual, posing as a reality of existence rather than a manifestation of the desire to increase profit in the post-industrial era.

Marcuse is concerned with technological rationality because it contradicts the supposed values of individualistic societies by undermining the concept of individual liberty to rationally pursuit self-interested goals (Marcuse, 1941, p147). Instead, under technological rationality individuals are convinced that profit-orientated values *are* individual values. Objects that embody technological rationality function to manipulate users to conform to this worldview; the user of a technics is in fact being used by the technics, and unconsciously consenting to their loss of individual freedom while simultaneously endorsing and stabilizing the socially-engineered value system of increasing profits.

Consider this view of objects as non-neutral in the previous example of the BMW assembly line; the bulking mechanical arm that is charged with positioning 70-kilogram doors also marks the locations where manufacturing workers must attach quarter-panels. The quarter-panels, having previously been pressed by a different machine, show corresponding markings, allowing the human worker to easily attach the part in the desired manner, similar to corresponding Lego blocks. Considering the claims of Marcuse, those machines are being guided by the values and desires of their social conditions (the BMW company's desire to construct and sell a *3 Series* car in order to create profit) while exerting power over workers by guiding their actions to achieve profit.

Using Marcuse's critique of modernity's failure to recognise the social influence of objects, Bilić analyses algorithms as non-neutral objects created by contemporary technology companies (Bilić, 2018). Algorithms and their computations, like assembly-line machinery, are human-invented objects and therefore the product of the social conditions of the creator society. Like an assembly line, algorithms are guided by values and in turn guide individual actions. To assume that an algorithm is somehow objective because its functions are computerized underestimates the ways that algorithms are programmed by designer logics that are particular to the creator society (Gillespie, 2016, p21, 23-4). Bilić shares Marcuse's concern that technics, in this case algorithms, undermine values of individual liberty and autonomy, concerns that are explored in the upcoming literature review critical of algorithms.

The multiple stakeholders

Technology companies that host text and media content online are often referred to as "platforms". Van Dijck, Poell, and de Waal define a platform as "a programmable architecture designed to organize interactions between users." (Van Dijck, Poell, de Waal, 2018, p9). Platforms create value through users' attention, which in turn retains users, creating user data and a better knowledge of the user that may be used to create profit (Van Dijck, Poell, de Waal, 2018, p10).

The non-neutral and guiding nature of algorithms becomes apparent when considering the multiple actors' that design how algorithms function. Bozdag describes algorithms that recommend content as "online gatekeeping services" (Bozdag, 2013). The recommendation algorithms that platforms create filter content to guide users towards certain types of content and away from others depending on the creator's desires. Bozdag problematizes approaches to studying these algorithms that concentrate purely on the desires of software designers or the computer software itself. According to Bozdag, algorithmic decision-making goes further than just machines or platforms, but rather involves a complex network of actors and influences including human moderators, software engineers, content creators, third-party government and adverting policies, market share competition, cultural trends, user manipulation, etc (Bozdag, 2013, p211-12). Bozdag argues that the presence of "algorithms running on machines" should not blind users to the many human biases that exist along the strands of this complex web.

These influences are similar to previous communication technologies, such as human biases in the reporting of news by the media, with platforms simply being an iteration involving more actors (Bozdag, 2013). Drawing comparisons with "traditional" media, Gillespie points out that what is considered as relevant or newsworthy is the choice an editor-in-chief (Gillespie, 2016a, p20). There is no independent measure for what is "relevant", the editor-in-chief's choices are value judgements informed by subjective experiences and knowledge of a field. Similarly, in the case of recommendation algorithms, a subjective value judgement must determine what is "relevant" to a particular user (Gillespie, Boczkowski, Foot, 2014, p175). Algorithms undertake this role in the case of news aggregation websites such as Google News or Yahoo! News, and the experiences and knowledge of the multiple stake holders noted by Bozdag inform those algorithms. In the case of YouTube, the company uses demographic data of users such as age, gender and location, and combines this with more granular data on an individual's previous watching habits such as a user's average amount of time spent on YouTube, the types of videos watched, and the type of device being used.

The satisfaction principle

The perceived objectivity of the computational functions of algorithms is the product of the recursive nature of algorithms (Beer, 2013). Algorithms provide outputs by processing input data. That input is an abstraction of the world, categorized by humans into data and code so that it may be computable by algorithms. Using data gathered on the user, an anticipated user profile is created in an attempt to predict the category of user active on a platform and "bluntly approximate" what is expected to be relevant to the anticipated user (Gillespie, Boczkowski, Foot, 2014, p174). It is impossible for algorithms to be *concerned* with any kind of objective relevance or truth, rather algorithms output recommendation that is expected to *satisfy* the user (Gillespie, Boczkowski, Foot, 2014, p182). Successfully functioning algorithms produce outputs that programmers desire and in doing so Beer identifies a slight-of-hand. Once the algorithms output is deemed desirable to certain individuals, the algorithm is framed as successful, and the original abstraction of the world into data and code is black boxed. This resembles Marcuse's argument that considering a technics successful conceals the rationality that motivates the technics.

To summarize, the input data is a human constructed categorization of reality and thus is prone to human biases. The output is only deemed successful at comprehending the world when it appears to satisfy the subjective desires of multipule stake-holders. Therefore, rather than algorithms being objective, all of their functions, inputs, and outputs, are the result of human bias, categorization and abstraction, none of which can be considered objective (Beer, 2013, p72).

Beer's concern is that as undetected algorithms and abstracted data become more embedded in our social and political systems, their manipulating nature is perceived less (Beer, 2013, p70). For example, as noted by Kitchen and Dodge, software models are designed to analyse the climate by converting theories of weather patterns into data to predict future patterns and influence climate change policy (Kitchen and Dodge, 2011, p30) (Beer, 2013, p74). Weather data is an abstraction of weather, a human-made measuring system that attributes numeric values to nature to better create patterns and predict future weather. Meteorologists use algorithms to predict future weather based on abstracted data of previous patterns, and the original abstraction of data is presented as a reality of weather. After the abstracted data becomes an objective truth of weather, the truth of the abstraction is affirmed when predictions are accurate and ignored as weather being "unpredictable" when inaccurate. According to Beer, the "objective" reality of algorithmic prediction becomes especially apparent when individuals act upon those predictions.

Imagine a young family plans a day at the beach after a local weather forecast announces a sunny afternoon. Upon arriving at the beach, the mother of the family notices incoming clouds (an unpredicted weather event) but decides to rely on the local weather report and stays at the beach with her family. Once the rain begins to fall, the family retreats to the car and abandons the activity, upset that the weather forecast was wrong. The next morning before work, the mother reminds herself to pick up an umbrella on the way out of the house, as the same local weather report has now announced afternoon rain. In the example, the character of the mother is largely reassured that the family's spoiled beach day was not a failure of meteorologists' abstract datapoints to accurately predict weather, but rather the result of the unpredictability of weather. Even after disappointment, the mother's actions remain influenced by her perception of the original abstraction of data as being an objective reality of the weather. Thus, she takes the umbrella.

The previous example obviously ignores the high accuracy of the majority of weather forecasting, varying levels of fear of being drenched in a downpour and assumes that people trust meteorologists. But the point being made is that predictions based on abstracted categorizations of the world affect human action.

In summary, abstracted data created from human categorization and bias and the algorithms that operationalize that data play an active role in social processes because they cause action in individuals while simultaneously rationalizing biased human categorization of the world (Beer, 2013, p72, 88). Algorithms and the abstracted data that feed algorithms are embedded in social systems and their capacity to influence human action is perceived as rational and objective, or not perceived at all.

While algorithms used to predict weather act to improve individuals' lives, such as planning outdoor activities, algorithms can be based on other less altruistic values. For private technology companies that rely on advertising to maintain constant revenue and growth, their algorithm designs appear to be considered successful when they hold user attention for the longest period possible. Unlike algorithms used to predict weather patterns that guide human decision making about outdoor sports or beach days, private technology companies attempt to guide human decision making to increase company profitability.

Controlling nature of the algorithm:

Recommendation algorithms function by guiding users' possible actions to desired ends informed by predictions based on previously collected user data. These functions have been heavily critiqued as undermining user autonomy by reducing users' choices (Brownsword, 2011; Bozdag, 2013; Dormehl, 2014; Schulte, 2016; Finn, 2017; Postigo, 2014; Gillespie, 2018). While these critiques could be made against any private technology companies that employ algorithms in their products, the majority critique the technology companies that control the largest tech market share: Meta, Amazon, Apple, Microsoft and Google. These companies are often referred to under the umbrella term "platforms" because the diverse range of products and services that each offer makes terms such as "online search engine", "social media network" or "online shopping network" importantly inadequate.

Internet platforms moderate user-generated content (videos, images, articles, items for sale, social media posts, etc.) to be circulated to other users based on data provided by users as well as captured from their online activity (Gillespie, 2018, p18-19). Platforms offer a moderation service rather than generating content and provide the service at no charge to the individual user. Effective algorithmic moderation adds value to the content so that it may be sold as a commodity to advertisers. In part due to this economic incentive, algorithmic moderation is now the main goal of platforms, rather than creating spaces that encourage user creativity (Gillespie, 2018, p41-43).

Gillespie identifies three content moderation types that are often used by platforms to host, organise, and collate user generated content (Gillespie, 2018, p207-8). First, *moderation* is concerned with the filtering and removal of content. Second, *recommendation* is concerned with organizing personalized content and putting trending content before users' eyes. Finally, *curation* is concerned with content featured on principle landing or home pages of a platform. In all three of these methods, platforms use available data and their algorithms to engage users most effectively for the purpose of keeping users on-site.

Objects have a performative nature because to function they must affect the user's behaviour (Dormehl, 2014, p136). Door handles demand to be gripped and turned, eye-glasses demand to be perched on the nose of the wearer, mugs demand to be kept upright to hold their contents. Algorithms are also performative in nature; they demand to be used to certain ways to function correctly, thereby successfully influencing the users' behaviour. The performative nature of algorithms shows when people use interfaces that they know, tacitly or otherwise, rely on algorithms. While using an interface (e.g. entering a query on Google, or speaking to Siri) users change the way that they type or speak (keywords, certain grammar) so that an imperfect algorithm may better understand and recommend what the user desires (Finn, 2017, p60). The algorithms affect the speech patterns and grammar of users to achieve desired results.

In this way, technology designers modify the behaviour of users by delegating specific responsibilities to the objects they create, encouraging users to obey the laws of an object in order for the object to properly function. Dormehl raises this feature of objects to question the agency of users consuming content recommended by algorithms. How platform users exercise agency when the design of recommendation algorithms allows little choice of deviation from output being recommended becomes an important issue to understand. This can be done through studying the processes of user quantification that recommendation relies upon.

Quantification of a user through data capturing, analysis, and organization allows the user to be processed by algorithms and consequently allows algorithms to predict user behaviour. Quantification of a user is realized through algorithmic processes of categorization. Categorization is a cognitive necessity to meaningfully comprehend the sensory input we experience from each passing second (Finn, 2017, p157). Capturing user data has appeared as a response to this desire to becoming intimately acquainted with a user. Gillespie's typology of moderation shows how platforms use listing, categorizing, organizing and ranking to better understand the world generated on their online platforms, as well as alter that world for their own benefit. The prediction capabilities of algorithms may be beneficial to users, however Brownsword warns that capabilities may undermine the autonomy of users by withdrawing the right of a user to choose (Brownsword, 2011) (Dormehl, 2014, p138).

Quantification of a user is a key goal of platforms that rely on recommendation algorithms. Schulte's (2016) work is concerned with the "predictive personalization" goals of platforms that rely on recommendation (YouTube, Netflix, Meta, Amazon). Predictive personalization quantifies user behaviour to curate an online identity for the user and subsequently align this identity with others that are identified as belonging to similar groups (Schulte, 2016, p250). Algorithms are designed to identify associations between users depending on the users' classifications. The associations algorithms make relating to the classification of individual users in certain demographics is based in a conservative logic that similar people are expected to act in similar ways (recidivism, guilt by association, genetics, etc.) (Gillespie, 2018, p109-110). Association and recommendation algorithms also take into account the individual user's behaviour patterns to serve content similar to what they have already consumed. Schulte suggests that instead of facilitating user experience, personalization functions of recommendation algorithms deny agency to users (Schulte, 2016, p250). Platform algorithms quantifying users for association and recommendation are driven by marketing desires and effectively limit users' possible experience on platforms.

These limitations are seen in users seeking content on platforms as well as in users that create content for platforms. Gillespie, Postigo and Finn identify a loss of agency felt by creators in the types of content that they produce that relates to the performative nature of algorithms. Postigo suggests that because the metrics used to measure and subsequently recommend content on YouTube motivate certain content creators to conform to creating certain kinds of "popular" content types, those metrics may in turn be limiting the variety of content on YouTube, and driving homogenous content on the platform (Postigo, 2014). This is the result of what Gillespie refers to as an "economy of popularity". A platform's desire to curate content to keep the largest number of users on-site means that metrics like trending and hotness (measures of content popularity) are common because they indicate increased user engagement with a site.

Gillespie claims that popularity is a shallow metric when deciding what content deserves to be promoted by a platform and undermines deeper types of engagement and collaboration between users (Gillespie, 2018, p201). The result is a lack of agency for content creators and users, the former feeling forced to create shallow content conforming to trends to remain visible, the latter being bombarded by this shallow content because it is believed to keep the user on-site. Information, whether artistic, cultural, economic etc., is consequently organized based on a company's definition of popularity (and repeat business) rather than other subjective or non-economic qualities (Finn, 2017, p157). The result of these tactics is a homogenization of content, like a market that demands a certain type of crop. Users are creating content specifically to be successful within a system that categorizes based on popularity, leading to standardized types of content.

In conclusion, users are "controlled" and "shaped" to fit within online identities limited by the metrics created by software designers and platform business logics. The metrics used to construct a user's online identity are selected by platforms to maximize profit (Schulte, 2016, p250). Algorithms therefore are expressions of power of platforms, and due to black boxes and perceived objectivity, the motivations of authority are hidden from users (Beer, 2017, p10). This can result in the perceived or unperceived loss of agency by all types of users on the platform due to the controlling nature of algorithms and subsequent homogenization of content. The orientation of platforms towards profit has been a recurring feature, and the following section will address the legitimacy of these concerns before moving towards more critical theories of platform capitalism.

The financial motivation to use algorithms to control

It has been established that recommendation algorithms influence user behaviour and consumption of online content. Algorithms are expressions of the power of platforms, and due to black boxes, the motivations of authority are hidden from users (Beer, 2017, p10). Considering this social power and the opaque nature of black boxes, multiple theories regarding the motivations of algorithm designers and platform owners have appeared. A number of these theories have concentrated on the economic motivations of platforms owners to guide user actions (Gillespie, 2016a; Gillespie, Boczkowski, Foot, 2014; Finn, 2017; Schulte, 2016; Pasquale, 2016; Mager, 2012; Feldman, 2017; Dormehl, 2014; Srnicek, 2016; Van Dijck, Poell, de Waal, 2018; Suboff, 2015, 2016, 2019).

In the contemporary, the categorization and subsequential hierarchization of information has been outsourced from experts to algorithms (Finn, 2017, p156). The goals of algorithms are constructed and informed by the goals or their owners. In the case of private platforms, these are business logics, with the goal being profit (Finn, 2017, p64). The explanation of business logics explains the shift of platforms towards personalized recommendation. Effective recommendation algorithms present content that a user will feel motived to consume, therefore fulfilling the private platforms desire that a user continue to use their service (Finn, 2017, p73). “Anticipation requires intimacy”, and so the best recommendation algorithms must rely on an intimate knowledge of a user’s previous behaviour so that recommendation may be personalized for that user (Finn, 2017, p75). This is achieved through the quantification of users.

Platforms are concerned with *knowing* their users so that they can better target advertising to those users. The message of an advertisement is inconsequential if an advertiser cannot find someone to consume the message. Data capturing has appeared as a response to this desire to becoming intimately acquainted with a user, and a marketplace of user data has emerged. Personal and behavioural data is scraped by platforms using third-party cookies, platforms consolidate their data with consumer data curated by data brokerage companies, to target advertising more effectively to users according to their consumption and socio-demographic behaviour (Smyrnaios, 2018, Online text no page numbers).

Srnicek also indicates that the main source of value within this contemporary platform economy is the refinement of users' actions on platforms into data, which is then used to advertise towards certain users and earn advertising revenue (Srnicek, 2016, p56). All activities of an individual online are captured and logged as data points and used to construct a social-demographic profile of an individual, which is subsequently used to identify patterns between larger groups of users (Van Dijck, Poell, de Waal, 2018, p34). Demographic and behavioural data gathered from users allows platforms to better advertise products to a target audience, thereby commodifying the social-demographic profile of an individual (Van Dijck, Poell, de Waal, 2018, p37).

Greater amounts of data allow platforms to create more accurate predictions of individual behaviour, thus a platform becomes more valuable with more users (Srnicek, 2016, p95). Users' are "controlled" and "shaped" to fit within online identities limited by the metrics created by software designers and platform business logics. The metrics used to construct a user's online identity are selected by platforms to maximize profit (Schulte, 2016, p250).

Data capturing informs platforms of behavioural trends, while also allowing platforms to manipulate the behaviour of users in real-time by influencing the types of content presented to users, and therefore influencing the "opinions and sentiments" of users (Van Dijck, Poell, de Waal, 2018, p37). In this way, according to Van Dijck, Poell, and de Waal, platforms shape the way their users live; platforms use their interface and algorithms to control what people may see and how they may interact, while limiting available choices and consequently user agency (Van Dijck, Poell, de Waal, 2018, p11). Quantification of a user through data capturing, analysis, and organization allows the user to be understood by algorithms, and according to platform business logics, consequently, allows algorithms to predict user behaviour.

Platforms face certain limitations when attempting to refinement user behaviour into data. Van Dijck, Poell and de Waal caution that the social-demographic user profiles constructed by platforms should not be tacitly assumed to be mapping an objective social reality of individual or group behaviours (Van Dijck, Poell, de Waal, 2018, p36). The data collected from user behaviour on platforms is limited by the platforms' interface. For instance, a user may react to a photo using six different responses, or share an article, or do none of these things, but only if those options are available. Platform design therefore limits the types of data that may be collected and weighed by algorithms. The data captured is not "raw", but rather "pre-cooked", and the platform interface plays a performative function in the possible social-demographic user profiles that may exist (Van Dijck, Poell, de Waal, 2018, p36). The data is therefore shaped by the platforms' interface, and then attributed importance depending on the platform's desires, meaning that the "platform perspective" is inscribed in the data from the beginning (Van Dijck, Poell, de Waal, 2018, p57).

This is well demonstrated in particular cases of platform categorization that Cinnamon defines as discriminatory (Cinnamon, 2017). The study finds that the process is an unjust misrecognition of users with the non-utilitarian goal of behaviour prediction (Cinnamon, 2017, p613-4). Profiling of users to best target certain audiences has been a part of advertising, marketing, and news media for centuries. However, the precision and speed of algorithms using behavioural data is more effectively targeting individuals and groups than ever before.

Qualitative interviews with experts involved in the development of search algorithms confirmed that the primary interest of search engines is to collect user and advertiser data to generate profit, which "'inevitably entrench[s] economic and political interests (. . .)'" (Mager, 2012, p777). The corporatization of the internet has led to the emergence of platforms that exercise power to encourage or supress certain speech for capital interests (Feldman, 2017). For Dormehl, these cases are the result of large companies making financially motivated decision to protect platform profits (Dormehl, 2014, p135). Private organizations that own platforms misrepresent and obscure the financial motivations of amassing data and recommending content by framing platforms as beneficial for society, causing users to become voiceless (Cinnamon, 2017, p615).

These arguments show a slight shift in literature from a critique of loss of agency, to a broader economic critique of loss of agency due to private companies' economic motivations. These arguments fall under many titles (i.e. "platform capitalism", "platform surveillance", "black box society", "knowing capitalism") and are concerned with the consequences of platforms economically motivated algorithm designs.

The "economic motivation" argument:

The generally accepted link between platforms' economic interests and algorithmic functions splinters into a range of critiques positing new forms of society, politics, capitalism, surveillance, and an overall decline of user agency online. These critiques are concerned with the role of platforms in the contemporary political and economic discourses occurring on and offline.

A more dominant section of algorithm literature is concerned with the capitalist nature of the companies designing algorithms, and how that nature is woven into algorithms. Platforms are examples of new intermediary capitalists that create and organize networks of public institutions, private companies, and individuals to then exploit their connections (Mager, 2012, p774). Mager describes algorithms as being shaped by capitalism while simultaneously entrenching dominant economic and political interests of technology platforms. Srnicek describes platforms similarly to previously mentioned authors; intermediaries that construct digital infrastructures allowing different users to produce online content as well as communicate with other users (Srnicek, 2016, p43). However, Srnicek theorizes that the emergence of platforms has created a new economy of commodities existing within an ideology of "platform capitalism". The main source of value within this contemporary platform economy is the refinement of users' actions on platforms into data, which is then used to advertise towards certain users and earn advertising revenue more effectively (Srnicek, 2016, p56).

The growth of certain platforms relies on a network effect and user retention. Network effect refers to when non-users feeling obliged to join a platform because members of their social circle use the platform, leading to growth (Srnicek, 2016, p46). The history of user action is used to classify and advertise to individuals, thereby creating advertising revenue (Srnicek, 2016, p95). Greater amounts of data allow platforms to create more accurate predictions of individual behaviour, thus a platform becomes more valuable with more users. More platform users mean more user action may be refined into data and the more valuable a platform may become, explaining platforms' tendency for monopolization (Srnicek, 2016, p95). Therefore, the profit generated by platforms requires that the most users remain on the service for the longest possible period. Competition in this new marketplace of platform capitalism is no longer based on competitive pricing because the services are offered for free. To remain competitive in such an advertising market requires ever increasing data extraction and ways of refining raw behaviour into more effective prediction models. This process relies on algorithmic associations between users and their actions (Srnicek, 2016, p97).

Srnicek notes that advertising has become precarious due to new ad-blocking technologies, government limitations on data brokering, and advertising profit declines in economic bust periods (Srnicek, 2016, p122). In response, platforms that rely on advertising are diversifying data collection techniques by investing in technologies that gather data on individuals' actions when they are not using the platforms; with smart televisions, wearable technology monitoring location and body functions, and in-home voice activation technologies (Srnicek, 2016, p122).

Based on Marx's theory of base/superstructure Zuboff claims that a new capitalist logic, "surveillance capitalism", has emerged in the contemporary information age. Zuboff agrees with Marx that the types of social relations possible within a particular period are limited by the predominant logic of accumulation of the period (Zuboff, 2015, p76). According to Zuboff, the current logic of accumulation is information (Zuboff, 2015, p77-8). Rather than being concerned with a labour surplus, like modern capitalists, contemporary capitalists are concerned with a "behavioural surplus" (Zuboff, 2016). Human behaviour online creates the raw material of data, which is then mined by machine learning algorithms to create the means of production of surveillance capitalism. Algorithmic manufacturing processes then convert the mined data into a consumable resource by organizing data so that it may effectively predict the future behaviour of humans online. These predictions are bought and sold on a "futures market" that trades in the anticipated behaviour of humans online, specifically, the believed accuracy of those future actions predicted by data sets.

Zuboff compares the capitalist model of platforms to earlier manufacturing forms. The comparison relies on platforms that do not charge for their services, platforms like Meta and Google. These types of platforms' profits come from advertising revenue. Advertising platforms host and curate user generated content so that other users may consume and interact with the content (Srnicek, 2016, p56). User behaviour on the platforms (clicks, likes, comments, ignoring content) are the raw material to be refined into data that is used to create a history of user actions. The history of user action is used to classify and advertise to individuals, thereby creating advertising revenue more effectively. It is in the interest of advertising platforms to offer their services free of charge. Unlike under former version of capitalism, advertising platforms do not need to earn money off their users so that they may in turn consume the products that they are creating, rather only survey user behaviour and construct online identities that can be bought and sold as predictions on separate markets.

Computing in the contemporary has become ubiquitous to the point that data collection is tacitly accepted (Zuboff, 2015, p77). The exponential advances of private technology industries have outstripped governments' ability to police ethically questionable behaviours of data retention and usage. Zuboff claims that this has led to "a lag in social evolution", where there now exists a dangerous and unjust "asymmetry in knowledge between tech companies and user population" (Zuboff, 2015, p84). Technology companies collect data irrespective of user privacy concerns simply because trailing government regulation has failed to regulate their actions. Whenever platforms are reproached for their actions, they may suffer some public backlash or perhaps pay a fine before continuing to use new practices that have yet to be classified as criminal. The approach allows the platforms to deny responsibility for their actions, due to a lack of regulation (Zuboff, 2015, p78). Simultaneously, as private companies that refine their intellectual property (algorithms) to compete on a free market more effectively, platforms are afforded great legal privacy regarding what they must and must not divulge of their data retention policies (Zuboff, 2015, p83). In this way, intellectual property laws are a foundation of black boxes.

Zuboff's second concern is the logical conclusion of a platform attempting to sell predictions on a futures market. Whilst prediction is effective, it often fails. Weather reports based on extensive data of atmospheric pressure systems, ocean currents, and yearly trends may fail to tell a person whether they should leave the house with an umbrella. Being able to influence the weather is more valuable than merely attempting to predict the weather. Truly valuable data, as in data that will derive the greatest profits, are types of data that can modify human behaviour to ensure even greater predictive power. Rather than offer options or the right to decision to users on a platform, the platforms will be more profitable by limiting the decisions and thereby algorithmically herding users towards results desired by platforms (Zuboff, 2019, p69-70)

This has caused, for Zuboff, the eruption of a second market that no longer trades in predictions but rather behavioural modification. “Actuations” in an “economy of action” are realized by “reinforcing”, “herding” and “conditioning” users towards certain ends by obfuscating possible actions available to them on a particular platform (Zuboff, 2019, p206). Zuboff titles this logical consequence of futures markets “instrumentarian power”, the power of knowing behaviour through data and using that knowledge to influence actions. For Zuboff, such power and the incentive to manipulate human behaviour on platforms threatens autonomy and influences the outcomes of supposed liberal democratic elections (Zuboff, 2016, p6; Allcott, Gentzkow, 2017). She calls for government intervention into surveillance capitalism to “reassert the primacy of liberal order in the 21st Century capitalist project” (Zuboff, 2016, p6).

The analysis of the economic motivations of platforms also extends to the methods that large technology companies employ to protect their assets against loss. Platforms purposefully inhabit a legal grey zone amid multiple roles. Critics claim that platforms assume this identity crisis of roles to limit liability and loss.

According to Pasquale (2016), online platforms assume the roles of conduits, content providers, and data brokers. First, platforms as conduits claim to present the actions and desires of their users, thereby relinquishing responsibility for unpopular user actions or views (Pasquale, 2016, p494). Platforms are obliged to include reporting functions so certain illegal content types may be flagged and removed. These are simple features that upon inclusion absolve platforms of responsibility for illegal content regardless of their effectiveness.

Second, platforms invoke a right to free expression as content providers. Unlike public utilities, private platforms reserve the right to arrange, present and filter user content or deny services to certain users. As content providers, platforms are under no requirement to align their terms and conditions of use with public institutions (Pasquale, 2016, p495). Companies may have guidelines but are not required to action breaches of the guidelines. Companies can also be motivated to claim violation of their guidelines and ban certain content to benefit the company. This is evidenced by the banning of certain apps or video content on platforms for a supposed breach of guidelines, while other content breaching guidelines remains available (e.g. pornography on YouTube, Apple's rejection of the application *Drones+*) (Pasquale, 2015, p63).

Thirdly, as data brokers, platforms reserve the right to collect, analyse, trade, and sell user data in exchange for providing the service (Pasquale, 2016, p495). This is a role like a stockbroker, except trading data collected on users to other companies for profit rather than a client's money on the market. Platforms change between the roles of conduits, content providers, and data brokers depending on the situation to avoid responsibility and ultimately attempting to maximize profits.

Dormehl states that users should not be surprised by algorithms that generate unexpected outputs or algorithms that appear to discriminate against certain types of input content too harshly. For Dormehl, these cases are the result of large companies making financially motivated decisions to protect platform profits (Dormehl, 2014, p135). Recommendation algorithms are more likely to strictly enforce community guidelines and risk discriminating against content that does not break the rules, rather than allow content to appear that may damage a company's relationship with advertisers, their public image, or their user base. These cases also show the weakness of recommendation algorithms to comprehend matters of ambiguity, enforcing binary rules more often that subjective standards (Dormehl, 2014, p141-2). The risk of economic loss associated with failing to identify undesired content is considered to be so high that most programmers design algorithms to broadly reject content identified as borderline, instead relying on a human expert to manually classify rejected content at a later stage (Alpaydin, 2016, p53-4).

Lash on hegemony: How power is exercised through algorithms in the contemporary

Lash makes the case that hegemony and hegemonic power in cultural studies has been defined as "domination through consent as much as coercion" (Lash, 2007, p55). Modern hegemonic power relies on ideologic discourses to convince subjects to consent to domination while also coercing subjects that refuse to consent (Lash, 2007, p58). This type of power is exercised *onto* the subject from *above* or *outside* through "constitutive" and "regulative" rules (Lash, 2007, p55, p71). Constitutive rules allow for games to exist; they establish the limitations of a game to which subjects must conform to rightfully be within the game, thereby constituting the existence of the game. For example, international law holds different criteria for a region to be defined as a state; these are constitutive rules that allow for a state or country to exist. Once a game has been constituted, regulative rules control the actions of subjects within the game (Lash, 2007, p71). Once a region is defined as a state or country, subjects wishing to exist within that constituted country are required to conform to the regulative rules of the country.

Constitutive and regulative rules are mostly transparent to subjects to allow for discourse and ensure subjects understand the goals of the rules, thereby encouraging consent. The resulting domination of subjects is through coercion and consent.

Lash proposes that hegemony can no longer account for the types of domination present in the contemporary, and instead proposes a new type of "post-hegemonic power" (Lash, 2007, p59). The source of post-hegemonic power is control of communication (Lash, 2007, p67). This theory usefully explains how users internalize the desires of the platform imparted upon recommendation algorithms and willingly attempt to conform.

Contemporary communication, especially online communication, takes place on platforms and is controlled by the limitations of those platforms. Communication on platforms is controlled by rules, however unlike regulative rules, contemporary rules of communication are mostly hidden from subjects. Blocking, connecting, and channelling certain types of content online is a way to control communications that exists pre-discourse. This type of domination of communication severs certain types of discourse at their root, rather than trying to coerce or convince compliance after a certain discourse is communicated. Power is coming from the capacity to block or control.

The post-hegemonic power of the platform acts from within the individual, rather than from outside or above the individual as in hegemonic power. Lash explains the influence of algorithms over user actions by conceptualizing algorithms as “generative rules”. Generative rules are rules hidden from players of a game that control a player’s actions (Lash, 2007, p71). Online platforms direct user actions using algorithms whose workings are hidden from users. The regulating functions of algorithms and the motivations for algorithms to regulate in a certain way are so well hidden from users that most of the population is unaware of participating in a “game” structured by platform providers. According to Lash, generative rules demonstrate the post-hegemonic capitalist power, a power that acts from within a subject to affect the subject’s actions without requiring a subject’s awareness or consent (Lash, 2007, p64, 71).

According to Beer, decision-making algorithms pose a threat to human agency. Machine learning software functioning to present or hide certain content represents a forfeiture of the human autonomy to choose (Beer, 2009, p997). Beer notes that there is a certain level of familiarity that users have with technology, that users are so familiar with how algorithms function that it is difficult to critically appraise algorithms (Beer, 2009, p995). This familiarity produces a “technological unconscious” where users are no longer aware of the black boxed nature of recommendation algorithms, the economics of particular platforms, the levels of involvement of different parties, data mining of users, the use of metadata in recommendation, how people come across this knowledge and how users use this knowledge to game systems, perceived or otherwise (Beer, 2009, p995). Although Beer endorses the dangers of invisible and manipulative technology for users, he proposes a solution that informs this research.

Counters to the argument of hegemony/post-hegemony:

Beer goes beyond previous theorists that critique post-hegemonic power by acknowledging that users may game systems by learning how they function. According to Beer, these instances are worth being studied. The following authors critique the perception of algorithms having an “all-powerful” nature to control users, and lead into a counter branch of literature concerned with users that are challenging and subverting algorithms to their advantage. This type of user is of particular importance when studying YouTube.

Van Dijck agrees with the thesis that users are being guided towards certain kinds of information and therefore those types of information on platforms proliferate. However, Van Dijck makes a valuable distinction between implicit (passive) users and explicit (active) users (Van Dijck, 2013, p160). The implicit user is unaware that she is algorithmically “locked” into certain actions on platforms and continues to use the site with a sense of agency. The explicit user is aware of the values and goals that platforms encode into their algorithms and attempts to learn more about these systems to resist algorithmic herding, even modifying code. The agency of the explicit user requires knowledge of not only the technology guiding user action but also the social, economic, and political motivations of platforms to guide user actions (Van Dijck, 2013, p171). These non-technical motivations are important for the explicit user because they reveal why mechanisms may function as they do, and therefore allow the explicit user to make a choice to either resist or conform depending on their personal values. Such a choice reveals a deeper form of user agency informed by knowledge of the mechanisms and context in which they function. The explicit user recognizes coercive types of technology used by platforms and may choose how she wishes to react to that information.

The absence of some videos and presence of others in a recommendation is an output that can reveal the criteria being algorithmically applied to user input (Gillespie, Boczkowski, Foot, 2014, p171). These criteria are the result of the judgments, expertise, and personal experience of platform owners, employees, and users. Gillespie stresses that these judgements become part of the algorithm and are then automated (Gillespie, Boczkowski, Foot, 2014, p178-9).

Gillespie proposes a conception of algorithms as entangled with practice (Gillespie, Boczkowski, Foot, 2014, p184). He accepts that algorithms are responsible for herding and controlling online behaviour not only by limiting visible options but also affecting how individuals create content for platforms. Individuals informed about the functions of recommendation algorithms become sensitive to the types of content algorithms react well towards and may use this information to leverage greater audiences. Unlike Lash, who proposes a similar idea as a form of contemporary hegemonic pre-cognitive domination of creators, Gillespie sees these individuals as being entangled in the practice of recommendation, taking part in the role of cultural gatekeeper along with algorithms, and understanding better how algorithmic decisions are being made.

YouTube recommendation algorithms are constantly modified and auto-modifying to best recommend relevant content to users. These modifications rely in some part on user feedback and user behaviour, which leads Rieder, Matamoros-Fernández and Coromina to question a research approach that concentrates narrowly on the technical functions of recommendation algorithms (Rieder, Matamoros-Fernández and Coromina, 2018, p53). According to the authors, such an approach refuses to recognize or account for unpredictable patterns of human behaviour. The researchers instead consider the actors involved with ranking (recommendation) algorithms, actors that exist within a "ranking culture" (Rieder, Matamoros-Fernández and Coromina, 2018, p52, 54). Users, content creators, algorithms and the platform are actors simultaneously building hierarchies based on ranking, processes that exist within a ranking culture. To fully understand the rank of a cultural product requires an examination of all of the parties involved in the creation of the hierarchy. These processes exist within a digital space that is governed by advertisement policies, copyright enforcement and censorship that are mandated by the platform while also being informed by other actors in the public and private sphere (Rieder, Matamoros-Fernández and Coromina, 2018, p65).

These approaches to user agency take into account the multiple stakeholders involved in algorithmic recommendation, the user and her social position included. This is, perhaps non-intentionally, a response to authors that have concentrated on the economic reasons for algorithmic action, or have suggested that algorithms represent a total elimination of human agency.

Tinkerers, hobbyists, and possibilities of local agency:

Going beyond the critique of economy-centric accounts of algorithms and agency, the concept of agency in technology and the existence of "tinkerers" or "hobbyists" provide useful directions to consider human agency as existing alongside technological advances.

Bijker considers the agency of people as being affected by the objects in their environment. For Bijker, a good example of agency is when an individual or a group identifies something as a problem and forms a strategy to solve for that problem (Bijker, 1987, p168). The capacity for an individual to solve a problem is limited by the techniques available in a given environment. A group of marooned travellers on an island may agree that bad weather is a problem and decide to build a shelter as a strategy to solve the problem. The island's ecosystem, any available tools and knowledge of shelter building are all parts of the castaways' environment that will affect the quality of their shelter.

Similar to this example, problem solving actions available to online users are restricted by the technological limits of the platform (Bijker, 1987, p169). Any user that wishes to interact with, produce within, or subvert the functions of a platform and its algorithms can only do so using the interface of the platform. The technological frame of a platform and how a platform's algorithms function is an environmental limit to users' agency to solve problems (Bijker, 1987, p169). But the environment also offers many affordances for agency.

When reading literature critical of the agency afforded by platforms, it would appear that users unknowingly forfeit decision-making to platforms' algorithms. Bijker suggests that we rethink agency depending on the field within which that agency may exist (Bijker, 1987, p172). While these environments may limit agency or guide user decision-making, they also provide users the tools to enact agency. This can be done by learning more about environment that platforms construct for users, and better understanding the functions of recommendation algorithms that guide us.

Revealing the operations of algorithms to the users of a platform is considered dangerous by platform owners due to the increased risk that users will attempt to work around or "game" the algorithms (Crawford, 2015, p87). Gaming recommendation algorithms is the purposeful altercation of content to take advantage of algorithms' usual functions, essentially hacking the algorithm for the user's benefit. This is not a common threat to platform owners due to the complexity of algorithms and the technical illiteracy of the majority of platform users. However, users that game algorithms do exist and have become an interesting site of user agency on social media platforms.

Before the period defined as Web2.0, the internet has been considered a democratic platform that allowed users to share information in open-source settings to fellow users (van Dijck, 2009, p50). This led to the creation of online communities sharing information regarding the internet itself, the technologies behind the computer networks, as well as novel ways to access and share information on HTML websites. Users that engage with online communities to learn and better take advantage of technology are what Van Dijck would call explicit (active) users (Van Dijck, 2013, p160). These are users that study technology so as to make more informed and agentic choices online.

Crawford makes a similar distinction between users, describing explicit users as “hobbyists” with the technical knowledge to understand and take advantage of algorithms (Crawford, 2015, p89). Hobbyists or tinkerers are consumers that attempt to open sealed technologies to better understand their inner working and possible alter their functions (Jungnickel, 2015, p1). Tinkering with products and materials in ways not anticipated by manufacturers is certainly no new concept. Modification, DIY approaches and re-circuiting were present in recipes, cars, HAM radios, and clothing altercations long before the internet (van Dijck, 2009, p51). Rather than just being a consumer of goods, the hobbyist is an active agent in the creative process of producing an augment product unique to the user. Embracing and tinkering with new technologies provides opportunities for agency to hobbyists.

Outside of social media

After the introduction of the automobile in the United States, women began tinkering with the technology in a proto-feminist effort to change the social perception of women as docile, subordinate consumers to consumers with “technological skill and ingenuity” (Franz, 2005, p72). Female hobbyist groups organized and shared information about car mechanics. Repairs and modifications of automobiles put women in more equal standing with men by subverting social expectations of the division of labour in the household. It was not merely cars that allowed for this agency, but rather women hobbyists' relationships with the object, and the empowering skills and knowledge that emerged from hands-on creative approaches to problems. Hobbyist informal self-education methods teach users not only how an object functions, but also how the companies creating that object function, as well as the markets that produce and sell those objects (Franz, 2005, p128).

The sharing capacities of the digital age have allowed for a greater dissemination of hobbyist literature. Unlike former hobbyists who sought out difficult to find textbooks on everything from sewing-machine circuit boards to Ford carburettors (Gates, 1976), the contemporary hobbyist rarely complains about the availability of resources explaining the innards of sealed technology. The open-source roots of the internet have enabled the creation of large communities of hobbyists working together to make black-boxed technology transparent, and to repair or augment technology (van Dijck, 2009, p50) (Barbrook, 2002). There are multiple examples of users finding affordances in technologies that are not directly perceived in their design but are discovered though other evidence revealed via tinkering (Tgaver, 1991, p80).

Franklin highlights user approaches to video games and technology that alter hardware and software to create new technologies and empower users (Franklin, 2009). Game artists manipulate hardware to change their original intended function as a form of personal expression. Hobbyists rewire circuitry in electronics to allow for new unintended outputs like distorted sounds or images. Online gaming communities have emerged around the practice of 'speed running', where players attempt to complete video games storylines as fast as possible. Speed runners use the programmed mechanics of the video game, however, subvert the original goals of game designers to advance more quickly. Speed runners purposely disregard narrative and quests, take advantage of broken or "glitchy" game mechanics and even strategically kill their character to advance more quickly. Communities of speed running hobbyists keep online score boards and hold events based on the subversion of the intended functioning of video games.

Game modification also challenges how video games were originally meant to be played through users' knowledge of computer languages. Users modify games by adjusting code to alter game mechanics, which can include new characters, new maps to explore, new creative game modes, new player abilities, novel scenarios and improved graphics (Wells, 2018). Modifiers often take suggestions from other users as to which modifications they would like to see and play. These modifications are then shared online in what Wells calls a "collaborative community" (Wells, 2018).

On Social Media

The growing use of algorithms to curate and recommend on search and social media platforms has led to a growing amount of algorithm hobbyists. The gaming of platforms' recommendation methods illuminates a competitive space between humans and algorithms (Crawford, 2015, p82). The gaming of audiences by content creators for attention and profit is certainly not a novel concept, however due to the sweeping appearance of search and recommendation algorithms users are understanding gaming in different ways (Crawford, 2015, p81).

The methods that are being used by some algorithm-gaming hobbyists resemble those that existed before computer algorithms. These methods are often co-opted from previous tactics depending on the algorithms' similarities to those previous ranking systems. While these methods of gaming recommendation algorithms certainly demonstrate explicit users' agency, in some cases they do so by undermining the agency of implicit users. For instance, reverse-engineering cyber-attacks demonstrated the capacity of users to take advantage of black-boxed algorithms to target and manipulate other users (Irani, Balduzzi, Balzarotti, Kirda, Pu, 2011). Malicious users exploit the functions of recommendation algorithms by creating fake accounts on social media platforms and manipulating demographic and tracking-based metrics to lure targets into cyber attacks. Such attacks rely on a sound understanding of the functions of platforms' recommendation algorithms and the types of input those platforms preference.

Empirical research also shows that widespread concerns about personal privacy and cyber-attacks online are understood by social media users and consequently affect their actions online. More than ever social media users appear aware of the privacy risks they undertake when using certain social media sites and actively inform themselves of available privacy tools as well as self-censorship of personal information (Casilli, 2013). Users with high privacy concerns on Facebook reveal less personal information on the site, demonstrating that education about the dangers of information sharing affects the amount of information shared (Young, A, Quan-

Haase, A, 2009). While these finding should not discount the inherent dangers of data-collection, self-education and consequent action shows that social media users choose how they are being perceived and to whom with a certain level of conscious control.

A two-sided example of the agency affordances of online platforms is the phenomenon of “fake news” on social media platforms leading into the 2016 United States Presidential election. Allcott and Gentzkow’s study of news article credibility on social media platforms finds that the entry level of credibility is much lower in online media markets due to the facility of publishing on intermediaries such as YouTube and Facebook (Allcott, Gentzkow, 2017, p214-5). Incredulous users are motivated to create purposefully misleading content due to advertising models that pay revenue based on people visiting sites (click-bait) (Allcott, Gentzkow, 2017, p217). Hoax articles often advancing or slandering certain candidates’ political positions gained great traction on social media. These are examples of users of sites tinkering with recommendation and human psychological to take advantage of platform algorithms while duping other users. The result is an example of agency and lack of agency; some users have the power to control the direction of information on platforms for monetary gains, others are unknowingly manipulated to follow those directions due to preferences for certain political parties and emotional reactiveness.

Relating to this study, it has also been shown that age demographics and the affordance of new easy-to-use technology reduces user agency on platforms. Fletcher and Nielsen identified user scepticism towards news recommendation algorithms on social media, despite most users admitting to not understand how recommendation systems rank content (Fletcher, Nielsen, 2018). In their study, the younger the user, the less sceptical that user was towards news recommendation algorithms on social media. Smyrnaios finds that some users are aware of algorithmically targeted advertisements based on user activity, leading to advertising becoming less lucrative for platforms (Smyrnaios, 2018). Advertisement blocking tools added onto internet browsers has increased, although it is difficult to conclude that this is an indication of user awareness of data retention, or simply users becoming frustrated with advertising appearing on-screen.

Social media sites that rely on users to post original content also oblige users to compete against one other to have their content seen. They tacitly encourage content creators to use methods to increase visibility (titles, tags, subjects, trending topics, cover photos etc.). A popular content type on YouTube is search engine optimization (SEO) videos for content creators. The videos are made by YouTube algorithm hobbyists and attempt to decode YouTube search and discovery algorithms to leverage viewers and gain popularity. Since “YouTuber” has become a career title, SEO videos have become prevalent. Most SEO videos discuss the metrics used by YouTube to recommend content. Because these videos are made for content creators, they are mostly concerned with the explicit metrics of audience engagement that creators have the most control over. In this way, recommendation algorithms heavily influence the types of content produced and the packaging of the content. Simultaneously, a tinkerer/hobbyist community has evolved in which fellow content creators share knowledge in exchange for recognition, advertising revenue and community engagement.

These empirical examples show that users can exercise agency in their online lives. Instead of seeing users as sheep being guided by algorithms designed to increase profit for online platforms, these empirical accounts describe an online space where users can exercise agency primarily through greater computer literacy.

Education in computer literacy:

Davidson suggests a solution to black boxes via education in computational literacy (Davidson, 2012). Davidson’s work is a response to complaints that students' attention spans have diminished due to contemporary technologies and the internet. Previous education systems favoured reading, writing and arithmetic because they were useful skills for the modern world. In the contemporary, these specializations are less demanded due to the prevalence of internet technologies. Davidson argues that early education should instruct students to be conceptually capable of understanding the internet as an electronic and material space built using code. Even students who will not continue into programming fields would build valuable computational literacy to help inform their future online interactions with platforms, algorithms, recommendations, data retention, and the online economy, which in turn will empower their inevitable online lives.

Methods:

The following proposals and limitations act as a starting point of this study's methodology.

Van Dijck, Poell, de Waal are concerned that "expert-based" recommendation no longer exists on algorithmically moderated platforms (Van Dijck, Poell, de Waal, 2018, p40, 63). "Expert-based" are those recommendations based on experience or knowledge that entail transparency and responsibility. Such editorial decision making has been entrusted to algorithms informed by user data, which is particularly concerning to Gillespie due to the opaque nature of algorithms' black boxes (Gillespie, 2016b). To deconstruct the functioning of a platform is to better understand they principles that govern user behaviour on that platform (Van Dijck, Poell, de Waal, 2018, p12). The authors advise that researchers attempt to access black boxes through reverse engineering, documentation regarding algorithms provided by platforms, leaked documents, or ethnographic research of engineers responsible for creating the algorithms (Van Dijck, Poell, de Waal, 2018, p41).

While some researchers want to understand what is in the black box, the complexity of contemporary algorithms makes transparency of function nearly impossible. Both black-boxed algorithms and open-source algorithms suffer from a lack of transparency due to their complexity, making algorithmic processes that lead to a certain output difficult to understand (Danaher, 2016, p253). The problem of transparency is exacerbated by deep-learning technologies that "auto-teach" algorithms to reduce outputs devoid of human rationality or expectation (Danaher, 2016, p262). Danaher is principally concerned that public decision making and governance are being forfeited to algorithms, theorizing that a system of governance that relies on algorithms to collect and organize information to inform decision making necessarily limits the ways humans may interact with one another (Danaher, 2016, p247). In the same way information is obfuscated from officials or activists by the hyperspecialized legal language and culture, the complexity of machine learning algorithms prevents functional knowledge of algorithmic choices through reverse engineering. To be able to see inside the black box would be to see millions of moving parts that do not appear to follow any previously understood human created pattern.

While some researchers are concerned with finding the exact operation of algorithms, due to the complexity of machine learning, this point is moot. Considering that algorithms are already operating, the effects of those operations appear to be more accessible and interesting for my own study. Particularly in cases of the effects of social media networks on the quality of the news delivery, user autonomy, and the ways that users may knowingly engage with algorithms.

Initial documentary research:

Documentary research is undertaken on the available information provided to the public by YouTube, Google, and independent sources attempting to reverse-engineer YouTube recommendation algorithms. This research is explicitly concerned with the outputs of YouTube recommendation algorithms garnered from publicly available materials. Specifically; the types of YouTube recommendation, YouTube's claimed desires and goals for their recommendation algorithms, implicit and explicit engagement metrics, the use of machine learning, and the commonly referenced metric of "watch-time".

Considering the secretive condition of black boxes (Pasquale, 2015; Gillespie, Boczkowski, Foot, 2014; Diakopoulosa, 2014), the benefits of obfuscation (Danaher, 2010; Pasquale, 2015), and the soft-autonomy and irrationality of algorithms (Sayes, 2013), such an analysis fails to explain algorithmic workings. Rather, the documentary research will provide a basis for better understanding YouTube's publicly stated reasons for and goals of recommendation. The documentary research provides a base understanding of how YouTube expects, or hopes, their algorithms to function and by doing so creates a fertile space to identify unexpected or undesired algorithmic activity.

Examining output:

Second, computer algorithms are recipes implemented by code to transform a certain problem, an input, into a certain solution, an output (MacCormick, 2012). The applications and intent of algorithms studied may be understood by examining the input and output (Beer, 2009, 2013). This stage of research relies on documentary and case study research of naturally occurring video and text data generated from YouTube and Google's publicly available information, as well as video data uploaded to YouTube by users. The goal is to better understand the types of input that algorithms are trained to privilege or deny, as well as the types of input that algorithms appear to privilege or deny. Input explicitly privileged by YouTube reveals YouTube's desires while also showing the failure of those desires when an algorithms misfunctions (Gillespie, Boczkowski, Foot, 2014, p171). YouTube users' reports garnered though uploaded videos reveal user expectations of the algorithms, and their praise of or dissatisfaction with algorithms when deployment does not occur as expected.

This level of analysis also explores how users optimize content to take advantage of the inputs that algorithms are trained to privilege, whether or not communicated by YouTube. Previous research shows that input privileged by YouTube algorithms encourages content creators to conform to "hot" or "trending" subjects due to monetary motivation (Fletcher, Nielsen, 2018). This suggests that recommendation algorithms, trending topics in the social sphere, YouTube, content creators, and content consumers are attempting to control or consume content that they perceive to be the most important. This analysis is interested with finding examples that counter the large literature that frames platform users as having little agency.

YouTuber informants:

Finally, the research explores how organizational practices and software infrastructure affect those who participate in YouTube sub-communities, specifically prevalent content creators (Beer, 2009). This level of research will use a judgement sampling method to select well-known YouTube personalities and conduct a thematic analysis of their experiences, reflections, praise and critiques of working with YouTube. Although the platform largely denies any responsibility for users that create content online (Manilève, 2018; Diakopoulosa, 2014), the study will treat these YouTube personalities like "employees" of YouTube; not necessarily because they work shoulder-to-shoulder with coders, marketers, or technicians, but because their experience behind the camera working with YouTube and its algorithms places these users in an informed or "native" position.

First, these content creators have a familiarity with the platform and the user-base that everyday users, small-audience content creators, and academics do not (Venturini, 2010). Second, these content creators rely on the economics of YouTube to earn a living wage and are obliged to be acutely aware of the functionality of YouTube algorithms. Third, preliminary findings suggest veins of resentment towards YouTube organizational practices that resemble employees of a company, despite YouTube claiming to *only* be an intermediary (Manilève, 2018). This level of analysis is concerned with how content creators play within and with the boundaries of YouTube organizational practices and software infrastructure. This involves YouTubers' levels of awareness of the prioritization, classification, association, and filtering functions of YouTube algorithms, user reflections on YouTube as a platform, algorithms, and their own personal patterns of content creation and consumption. This level of analysis provides a perspective that cannot be accessed via YouTube public communications or the researchers' remarks about the absence of some videos and presence of others on the site.

These levels are separated for methodological reasons because they will make analysis easier. Ultimately, they are concerned with a consistent object of study and provide a guide to better analyze this object of study. To comprehend the full extent of a controversial arena requires an identification of actors (YouTube, YouTubers, advertisers, lawmakers, consumers, etc.), and the non-isolated nature of those actors (Law, J, Lien, 2011; Law, Singleton**,** 2005). These three levels of analysis attempt to do so.

On controversies:

Controversies occur when actors conflict upon a certain subject and can no longer ignore the conflicting ideas of opposing actors (Venturini, 2010, 263). The complexity and fluid nature of collective life is based in the conflicting desires of individual and group actors that crave stability. The construction of collective existence is in controversy, and therefore those controversies that are most visible during a certain period in a certain location make visible conflicting group positions and therein make visible the construction of the collective existence. Controversies involve human and non-human actors. This demands that multiple opinions must be taken into account, however does not mean that all actors must be represented to the same level. The influence of actors must be considered; statements or positions shared by certain people in a controversy receive more attention than marginal positions, actors that command a higher level of attention play a role in shaping the debate surrounding controversies and thus have a greater influence. This is the justification for judgemental sampling of more influential YouTube content creators. Controversies are best when they are recent and mainstream because they are open for public debate.

Research that targets controversies must take into account that it is the actors who make the controversies, the actors that own those controversies, and this ownership must be respected as well as be a source of knowledge. YouTube user accounts provide a privileged look at networks that a researcher can never know as well as the confidants. YouTubers (YouTube users that post content online, sometimes professionally) are therefore studied as authorities of YouTube.

Methodology:

The study uses a semi-inductive thematic analysis method to identify patterns in algorithmic functions and the discourse surrounding algorithms, organize patterns into major themes and sub-categories, and analyse the themes as representations of the data set (Braun, Clarke, 2006; Kuckartz, 2013).

36 video files uploaded to YouTube between December 22 2014 and November 30 2018 were selected for analysis using a judgemental sampling method. 26 video files were created and published by 17 non-YouTube affiliated entities. 10 video files were created and published by three YouTube affiliated entities. Of the 17 non-YouTube affiliated entities, nine creators were independent, and eight creators belonged to production companies.

Preliminary video files were found by searching the keywords "YouTube", "Algorithm*", "Recommendation*", and "Subscriber*" in the search/query bar of the top 100 YouTubers by subscribers as represented by social media analytics and statistics tracking site SocialBlade.com. Only independent YouTubers and YouTube personalities belonging to a production company were selected for analysis. Record labels, music producers, media and entertainment companies, celebrity accounts, and accounts collating already published content were excluded because these entities use YouTube to leverage viewers, host videos, and add value to content that otherwise can exist without the intermediary platform. These types of accounts do not engage with

YouTube culture or the site as employees, but merely take advantage of YouTube as a platform to share non-native YouTube content.

Once controversies related to recommendation algorithms were identified, a snowball sampling technique was used to gather further opinions on trending controversies from other YouTube and non-YouTube affiliated entities. The larger themes identified in the literature review of the rationality of algorithms, content personalization, and content suppression were assumed to be of importance before initial coding of the data was undertaken. Optimization and freshness were themes identified after the initial coding of the data.

The analysis identifies examples of user agency that emerge in concert with the user's environment as theorized in the literature presented in the theoretical framework. These users, sometimes referred to as tinkerers or hobbyists, play an active role in creating content and recommendation algorithms through the sharing of information and self-education. This finding contradicts the definitive framing of algorithms and recommendation as undermining user autonomy, which exists in critical algorithm literature.

Background of YouTube Recommendation algorithms:

Home Page	Landing page of YouTube.com, lined with personalized recommendations based on the users watch and search history (subscription videos, popular videos, videos that perform well with similar viewer demographics etc.) Recommendations are comprised of new videos/channels as well as subscribed content. (V12; V16) Home page recommendation account for 60% of all video clicks from the home page (Davidson et al, 2010, p296)
Search/Query	User provides a query into a search tab with an autosuggestion function and is returned a list of videos that refresh via scrolling. The user query provides YouTube context to recommend relevant content, and the algorithms use the metadata in content titles, descriptions, tags, as well as the average performance of content to rank results. (V12; V14)
Watch Next	List of videos that appear to the right side of a video currently being watched. Watch Next recommendations drive large amounts of engagement on YouTube. Recommendations are informed by search queries and the additional context of the video being watched to recommend videos with similar metadata, viewers, and channel content. The recommendations take into account user history, subscriptions and trending topics. Watch Next recommendations are personalized to the user and may not be directly related to the video being viewed. (V12; V15)
Trending	Accessed through a drop-down menu. Trending compiles new, well preforming videos (high view velocity) that are broadly appealing to a wide audience. View velocity is judged by the amount of views that newly published content garners in the first days since publication, judged as a percentage of the publishing channels total subscriptions. Trending recommendations take into account the users' location, rising topics (both on YouTube and Google), and aims to recommend popular and novel content. (V12; V13; V17)

Table 1. Types of recommendation on YouTube

The Advent of Watch-Time:

In 2012, YouTube announced to content creators a key change in their algorithm to better account for radical variations in video view-counts (The YouTube Team, 2012). Previously, to identify popular content, recommendation algorithms relied on the implicit measure of view-count. This was quantified in clicks; a video's total views were measured by how many users clicked-through a video. YouTube noticed that this measure did not consider user engagement, as it could not measure whether a user actually watched or enjoyed a video. The metric was also being gamed by content creators to increase views. Misleading thumbnails or titles on videos lead to audience clicks even though the viewer would quickly navigate away from the deceptive video. Recommendation algorithms that do not account for the consumption patterns of audiences once they have landed on a specific video cannot identify the content creator's deception and are thus duped/games.

The changes to related and recommended videos put in place by YouTube in 2012 instead favoured watch-time. Watch-time is an implicit measure of audience engagement with video content calculated as how much of the video played before the user navigated away from the page.

> *"While we'll still be looking at clicks, engagement will become the leading indicator for serving these videos"*
> *"What matters is that your audience stops clicking away".*
> - The YouTube Team, YouTube Creator Blog, 2012

The blog post is important because it marks a shift from explicit measures of engagement to implicit measures. Rather than rely on measures where the user exercises agency to indicate what is important to him or her (clicks, likes, or comments), the website began to favour viewer retention measured by viewers' total time on site. By favouring these metrics assumptions about what is important to persons is made on their behalf by using information about their behaviour. People are engaged when they consume content, instead of when they explicitly indicate their engagement.

“The YouTube Algorithm”:

Matt Gielen & Jeremy Rosen published blog posts to YouTube SEO website *tubefilter* that analysed both creators’ channel analytics to better understand what they title “the YouTube Algorithm” (Gielen, Rosen, 2016; Gielen, 2017). This was to leverage YouTube’s black-boxed recommendation algorithms through reverse engineering. The blog posts mark an important moment in the history of creator led reverse engineering of YouTube ranking and recommendation algorithms because of its effect on the YouTube creator community. The posts instantly became a major topic of discussion and lead to an increase in YouTube content creators discussing “the algorithm”.

They estimate that the watch-time metric accounts for 85% of recommendation algorithms actions. Watch-time is separated into more granular measures: View duration, video length, session starts, session duration, and session ends.

Metrics	Estimated Weight	Description	Initiated by
Session starts (Video and channel):	45%	If viewer begins session on YouTube on a particular video/channel (i.e. the video “brings” the viewer to the site).	Viewer
View duration (Video and Channel average):	30%	How long viewer remains on a video.	Viewer
Upload frequency:	15%	How often a channel uploads content.	Content creator
Session duration:	5%	Total time viewer spends on YouTube in one sitting.	Viewer
Session ends:	5%	If viewer ceases YouTube session on a particular video (i.e. the video “sends” the viewer away from the site).	Viewer

Table 2. Watch-time (85%) (Gielen, Rosen, 2016)

Gielen and Rosen also attempt to explain the importance of several other implicit engagement metrics not shared in the original 2012 YouTube creator studio blog post. They estimate that the “relevancy” metric accounts for 15% of recommendation algorithms actions. Relevancy is separated into more granular measures: Playlist adds, news (“freshness”), closed-captions, comments, titles, shares, likes, tags, descriptions.

Metrics	Estimated Weight	Description	Controlled by
Playlist Adds	18%	If the content is part of, or has been added to, a playlist (curated by content creator or viewer)	Viewer/ Content creator
New (“Freshness”)	18%	Recentness of published video and relevancy to trending topics	Content creator/YouTube/ viewer
CC/ Auto Gen CC	18%	Published closed captions/auto-generated closed captions	Content creator/ YouTube
Comments	12%	Amount of viewer comments on video	Viewer
Title	12%	Video title optimized for search and recommendation	Viewer/ Content creator/ YouTube
Shares	6%	Amount of times content shared by viewers to other (social) media sources	Viewer
Likes	6%	Amount of times content liked by viewers	Viewer
Tags	6%	Video tags optimized for search and recommendation	Content creator/ YouTube/Viewer
Description	6%	Video description length, optimized for “tagged” language	Content creator

Table 3. Relevancy (15%) (Gielen, Rosen, 2016)

Viewers, content creators and YouTube have varying levels of control over each metric used as input for recommendation algorithms. First, viewer-controlled metrics are measures ultimately decided upon by the viewer; how much of a video a viewer chooses to watch, whether they stay on the platform or leave, explicitly engaging with a video by liking, sharing or commenting, etc. Content creators may try to influence these metrics to increase engagement. For example, the content creators appeal to viewers to “like, comment and subscribe”, sometimes before even consuming the content because view duration commonly drops after the opening minutes of a video. When a creator like Philip DeFranco asks viewers to subscribe to his channel and like his video, he is attempting to increase viewer-controlled metrics of engagement that he assumes YouTube recommendation algorithms use as input.

Second, content creator-controlled metrics are those ultimately decided upon by content creators; the length and content of video descriptions, or whether a content creator chooses to publish closed captions.

The remaining metrics appear to be a combination of YouTube, content creators and viewers. For example, the tags a content creator chooses to include on a video are influenced by trending topics that many viewers may be searching. These topics are generally related to external sources influenced by pop culture, politics, national or international events, recent films, natural disasters, sporting events, YouTube controversies, terrorist attacks, popular conspiracy theories, etc. These trending topics are socially and culturally informed and lead viewers to search certain queries, while also leading to greater recommendations of certain tags or titles, and therefore greater recommendations of certain videos that have optimized for those tags or titles. These have a snowball effect, and lead to recommendation trends that can only last for a period of time (e.g. Trump inauguration, fidget spinners, 2017 Las Vegas shooting, gender equality controversies, super bowl advertisements). These types of events that happen outside of YouTube (and some controversies between content creators that emerge from within the community) lead to greater traffic to certain types of videos. Viewers are enticed to search for that content, YouTube is enticed to recommend that content, and content creators are enticed to create and optimize for that content. The result is an assemblage of control over the types of content created, searched, and recommended.

Metrics are useful to content creators because they aid in search engine optimization efforts. However, considering the competitive nature of the platform, and the large amount of control audiences and YouTube appear to have over content suggests that content creators cannot simply convert knowledge of these metrics into greater recommendation efforts. Although a content creator can refer to the amount of likes a video has received as an indication of success, how long each of the users spent on the video, and what content the user watched before or after their video, appear to be important metrics that are far less easily identifiable to creators.

These blog posts published by YouTube and SEO experts are often cited by creators as a starting point for “the algorithm” controversies that followed. Recommendation algorithms would continue to change the relationship between those making, those ranking, and those consuming content. Recommendation algorithms remain opaque on a business end but become clearer when consulting content creators. Creators rely on the site for their wellbeing, and the recommendation algorithm is the key to success. Their failures and victories with YouTube recommendation algorithms assist a greater knowledge of recommendation algorithms and social media platforms themselves.

Machine Learning:

The content analysis explores controversies occurring after the publication the 2016 article "Deep Neural Networks for YouTube Recommendations" by YouTube software engineers Paul Covington, Jay Adams and Emre Sargin. The article is a landmark in the study of YouTube recommendations because, for the first time, creators and users alike were allowed a look at the guts of the recommendation black-box. A group of data and machine intelligence experts from Google explained the two tiers of collection and ranking involved in a regular YouTube query.

The problem of moderation at scale is noted by most online intermediary platforms (Pasquale 2015, p65; Diakopoulos, 2015; Gillespie, 2018). The engineers outline the difficulty in creating effective recommendation algorithms due to the sheer quantity of videos uploaded to the site, estimated at 400hrs per minute (Brouwer, 2015). Google and YouTube use deep learning to solve this problem of scale. When a user lands on the YouTube home page, searches a query, or watches a video, two separate neural networks first generate candidate videos from the total YouTube corpus before ranking those candidates from most to least relevant for the user (Covington, Adams, Sargin, 2016).

First, the video candidate generation neural network uses data on past user activity as well as demographic indicators of the user to construct an online identity to classify the user in larger consumptions patterns and attempt to predict entertainment tastes (Covington, Adams, Sargin, 2016, p192). This level of candidate generation relies heavily upon the aforementioned watch time metrics, confirming that the desired objective function of the neural network is to achieve greatest user watch time.

The second neural network assigns scores to each video in the pool of generated candidates to rank them in order of "most suitable for the user" (Covington, Adams, Sargin, 2016, p192). The weight of each score relies on data of the user's past activity, as well as features of the video described in the relevancy metrics (title, tags, descriptions, audience engagement etc.).

The final metric used is "freshness", which, to a certain extent, assigns greater weight to newer content published by channels frequented by the user or content that is generally preforming well on the platform. Previous testing conducted by YouTube demonstrates that users prefer newer content, although this must be balanced with relevancy, a balance not made entirely explicit in the article. The output for the ranking neural network is a few dozen videos selected from the candidate generated output that are presented in order of "most relevant" (most likely to be clicked-through and watched by user) to "least relevant" (least likely to be clicked-through and watched by user).

Expected Watch-Time Per Impression:

The final factor that influences the ranking of videos is related to the expected click-through rate (CTR) per impression. It is hard for the algorithm designers to know whether a user is satisfied by recommendations unless they explicitly "like" a video. This rarely happens. Watch-time somewhat takes care of this by assuming that a video with a longer average watch-time must mean users are on average more satisfied with that video than another with a lower average watch-time. However, YouTube cannot only rely on watch-time, but must also consider the CTR of videos. A video with a high average watch time (how long most people remain on a video), however a low CTR per impression (how often people click on the video when recommended), may have an overall lower total watch-time than a video with low average watch time but a high CTR. Therefore, if a user does not click on content that appears as output of the recommendation algorithms, this acts as input for ranking algorithms and futures recommendations are adjusted to suggest different content to the same user. This appears to be taking place on a channel level; if a user does not click on certain content, the channel that produced said content will be recommended less in the future. More on this to follow under "subscription burn".

YouTubers on Watch-Time:

The results published in these blogs and articles rippled through the YouTube content creator community. Discussion of "the algorithm" concentrated on watch-time, and the effects of watch-time on various types of content. *H3h3 productions* noted that the introduction of watch-time led to the demise of channels that create labour intensive content (V2). Animation channels mostly publish shorter content infrequently due to the demands of animation. A recommendation algorithm promoting videos or channels based on the amount of time they keep users on site preferences longer videos, as these have a higher average total watch-time, even if the percentage of the video watched on average by each user is much lower than animation content. YouTube SEO and marketing channel *Brian Dean* stresses that due to the weight of watch-time metrics longer videos will often outrank shorter videos and encourages content creators to produce videos between 8 and 15 minutes in length (V19). The type of hardware used to access and consume YouTube videos further affects watch-time. Mobile users often watch YouTube for shorter periods of time, and will therefore be recommended shorter videos, while desktop or smart-TV users watch for longer periods of time and will therefore be recommended longer videos (V31). These remarks from YouTube experts allow for a greater knowledge of the effects of certain elements of the platform's recommendation, and therefore a better idea of the black box between input and output. It leads into the finding of the insignificant weight of explicit metrics in recommendation, and in a larger sense the insignificant weight of explicit user satisfaction indications to recommendation algorithms and their parent platforms.

Results:

1. Personalization for Users:

Personalization is the creation of online identities to anticipate and control user behaviour. Users are identified by their unique device IP, cookie text files or by logging-in to an account. Once a user is identified, the user's current and past data is organized to create an online identity based on their behaviour. Personalization identifies the user through classification and association, and the resulting algorithmic recommendations shape consumption habits of users. The behaviour of a person consuming content on YouTube converted into metrics that create an online identity for that person. If the person knows which metrics are most valuable to recommendation algorithms they may be able to better control the types of content being recommended (Schulte, 2016, p250).

Subscriber Burn:

YouTube allows users to create a free-of-charge Google account to subscribe to content creators' channels. Videos from subscribed channels will then appear in a section of the user's account titled "Subscription feed". YouTube will also send notifications of well preforming videos or "highlight" videos from the channel to its subscribers. In subscription settings users can decide on the amount and type of notifications they are recommended. The number of subscribers a channel has is considered a quantified measure of the channel's success, and content creators often use subscriber numbers to compare themselves with peers.

Towards the end of 2014 YouTube content creators began to note drops in subscribers and views. Video game vlogger and YouTube SEO expert *The Game Theorists* referred to the phenomenon as "subscriber burn" (V1). Subscriber burn refers to the phenomenon of YouTube not notifying subscribers of new videos, content creators receiving fewer views, and in some cases, subscribers being unsubscribed from channels. *The Game Theorists* reveals that this is a major concern for content creators as they rely on subscriptions for a stable amount watch time.

Subscriber burn is the result of YouTube curating and moderating subscribed content. Similar to other social media platforms, YouTube personalizes subscribed content to present videos from channels that appear to engage the user. If users do not click-through impressions from a certain subscribed channel often enough, YouTube assumes the content created by this channel is no longer of interest to the user. Despite a user's active subscription to a channel, recommendations from the channel to the user are reduced because the recommendation algorithms do not anticipate that the user will consume the content. The result is "subscriber burn".

The conversation around subscriber burn increased after YouTubers *PewDiePie* and *h3h3 Productions*, among others, created videos complaining about reduced views due to subscribers not being notified of new content (V3). YouTube community managers initiated a survey to better explore claims that users were being unsubscribed from channels, claiming "YouTube does not unsubscribe users from channels" (Marissa - Community Manager, 2016). However, community managers did not account for "inactive subscribers". Inactive subscribers refers to user accounts with subscriptions but exhibit no behaviour. These would often be YouTube accounts that users forgot about or no longer use. Were YouTube to decide to delete inactive accounts after an extended period of inactivity many YouTube creators would notice a loss of subscribers, however considering the accounts were inactive this should not affect overall views.

Multiple YouTube channels concerned with SEO, marketing and channel growth attributed the phenomenon of subscriber burn to CTR (V10; V19; V29; V31) (Covington, Adams, Sargin, 2016). They suggested, along with *YouTube Creators [Creator Academy]* (V16), that producing videos in a niche genre aids consistent views because users subscribed to a channel are presumably interested in that type of content and are less likely to skip published videos. Variety programming on a single channel leads to subscriber burn, because subscribers only consume content they are interested in and therefore skip videos. Thus, indicating to recommendation algorithms that channels creating niche content repeatedly engage and bring users back to the site. For example, if a YouTuber publishes health and beauty content to his channel, but occasionally publishes video game commentary, it is expected that subscribers who like health and beauty content will not click-through a video game commentary video. The failed click-through becomes a measurement used by recommendation algorithms, and future health and beauty videos created by the YouTuber may not be recommended to users that do not like video games.

Channel subscription is one of the few overt indications from users to recommendation algorithms of the type of content users wish to consume. YouTube software engineers largely design recommendation algorithms to ignore whether a user indicates desire to watch certain videos. Engineers are more concerned with how much time channels and videos keep the user on site. They are more concerned with the performance of a video with a certain audience than with any overt measure of an individual subscribing to a channel (V20). *YouTube Creators [Creator Academy]* stresses that the history of the user and the categorization of that user as having similar tastes to others play a more important role in recommendation than subscription (V16). Personalization of recommendations is based on the videos watched by the user, as well as the videos not watched by the user (i.e. failed impressions).

Personalization:

Recommended content is an algorithmically generated value judgment based on the categorization of a user as belonging to certain groups, relying on points of data gathered self-reported communication with the user and user behaviour (Gillespie, Boczkowski, Foot, 2014, p175-6). If programmers decide that a certain type of video preforms well for a certain category of audience based on metadata, the programmers design algorithms to rank the video higher in recommendations for users identified as belonging to that audience category (V12) (V16). Therefore, the categories that the audience is identified as belonging to and the categories that are identified as enjoying certain types of content function as inputs for recommendation algorithms.

Audience categorization and association is based on the principle that individuals identified as belonging to similar demographic, group, and identity types will act in similar ways and hold similar preferences (Gillespie, 2018, p109-110). Programmers gain their understanding of the user through quantifying millions of user interactions. YouTube user information and consumption habits are used to curate an online identity for an individual, allowing the person to be understood algorithmically (Finn, 2017). The identity is then aligned to others that are categorized as belonging to similar groups (Schulte, 2016, p250). YouTube engineers use machine learning systems to classify individuals as belonging to pre-existing categories (race, sex, gender, location, age, etc.). Due to this, the subjectivity of human categorization along with any bias related to that categorization is imparted onto the classification functions of algorithms (Diakopoulosa, 2014, p401). The algorithms' functions are rooted in the programmers' very human, subjective categorization of user tastes and associate relationships between individuals based on that categorization. Personalization is thus a big-data solution to the difficultly of knowing the actual users by "bluntly approximating" the anticipated user based on degrees of similarity with others (Gillespie, Boczkowski, Foot, 2014, p174).

User history also includes search queries that provide a greater context for what the user has actively sought in the past (V12). Combined with CTR versus impressions, YouTube uses metadata to assume the types of results that are more likely to satisfy certain categories of users in search, which are then incorporated into recommendations. Therefore, any user autonomy in selecting content is reduced or ignored as an ineffective input for recommendation algorithms.

The home page functions under similar principles. The YouTube home page (www.youtube.com) features recent and past videos from subscribed channels. However, engagement has been shown to increase when users are recommended "fresh" or new varied content (V12) (Covington, Adams, Sargin, 2016). Recommendation therefore takes into account the engagement habits of users categorized as belonging to a similar online identity category, as well as channels and videos that are related to past search queries and current subscriptions (V12). These metrics are combined with trending topics and HTTP cookies (data records of individuals' previous activity on a web browser) to recommended content. When a user does not have an account, trending topics and HTTP cookies are more relied upon to recommend content. Once a query has been entered by a user without an account, or an impression is clicked through on the YouTube landing page, data will continue to be collected to better categorize the user and relate future recommendations to past logged activity.

These findings demonstrate the relative weakness of subscription as a reliable metric in recommendations. While it is effective as a base to begin identifying the edges of a user's online identity, it is a buoy in an ocean of data retention. The user's behaviour and the behaviour of others similarly categorized carries more weight than the claimed desires of users.

Subscription Optimization:

Subscription optimization is a specific type of personalization used by YouTube to recommend content to users. The subscription "feed" is a menu that combines all of a user's channel subscriptions, excluding any content not subscribed to by the user. Videos on the subscriptions feed are arranged in a personalized order, not chronologically, based on users' past viewing habits. YouTube defended subscription feed personalization because "some viewers are able to more easily find the videos they want to watch when we order the subs feed in a personalized order" (Team YouTube, 2018). *Philip DeFranco* notes that YouTube is conforming to algorithmic curation of content similar to platforms like Facebook, Instagram, and Twitter in a bid to "increase engagement" (V27). Consequential increases in engagement are proof for YouTube that personalized recommendation more effectively holds attention. In an economy based on the quantity of time a user spends on site, these algorithms are framed by platforms as successful (Beer, 2013, p72).

This is problematic for channels with slower publication schedules because they seldom bring users on site. Both *DeFranco* and *h3h3 Productions* view the change as disastrous, concerned that the subscription feed was one of the few features of the website that allowed users to curate content (V26; V27). A user's choice to subscribe to a channel already appears to be mostly disregarded by YouTube. The platform, like others, puts more weight on the viewers' past habits and actions, categorization of the viewer, the short-term performance of videos and the videos capacity to retain an audience (V21). Recommendation algorithms account for how users arrived at a certain video and whether videos lead to users navigating away from the platform. These are combined with other implicit metrics to judge a video's audience retention capacity. Ultimately, recommendation algorithms consider content "good" when it keeps users on site for the longest period possible. This shows a distinction between the curation of old media and social media, conforming to arguments that new media must be considered as very different to the curation of television and broadsheet equivalents (Pasquale, 2016; Gillespie, 2014, 2018). A subscription to a daily or weekly newspaper that is curated by an editor-in-chief is different to a subscription to a creator whose content will then be curated for the user by YouTube.

Ignoring subscription, an overt indication of individual desires, disregards human autonomy to participate in their consumption patterns. The existence of subscription accommodates the illusion of choice. The subscription feature conceals the guiding and embedded nature of algorithms online by offering weak capacities of agency to users. In doing so, companies seemingly empower users while algorithms continue to function otherwise, despite YouTube being aware of the subscription intentions of users. The guiding nature of the algorithm is hidden in the shadow of choice, thus users see algorithms and their guiding nature less (Beer, 2013, p70).

Filter Bubbles:

Filter bubbles or echo chambers have been noted as concerning effects of algorithmic recommendation (Pasquale, 2015, p79; Allcott, Gentzkow, 2017, p213). Allcott and Gentzkow found an ideological segregation amongst online users that they partially attribute to algorithms programmed to recommend similar types of content to users (2017). Content creators, incentivized by ad revenue, attempt to bait users into consuming their videos by creating politically partisan and even slanderous content. Recommendation algorithms continue to recommend similar content to users, and users become segregated from different or competing positions. This results in filter bubbles, "insular" online spaces that "reinforced prejudice" algorithmically (Pasquale, 2015, p79).

The effect of filter bubbles or echo chambers was not remarked in this study. However, this study's finding that algorithms are engineered to categorize and recommend according to previous consumption patterns and the consumption of those identified as peers does support the hypothesis of filter bubbles. The ideological and partisan segregation of news consumption and insularity causing reinforced prejudice both theoretically fit into the above findings. Platforms that design algorithms to classify individuals into abstract groups based on implicit online micro-behaviours are motivated to present content that confirms users' previous biases, and thus will keep users on site for longer periods of time. Informants may not have commented on the effect of insular consumption because the theme appears to be so prevalent in public discourse that it has becoming a tacitly accepted norm of platforms.

2. Optimization by Content Creators:

Search Engine Optimization (SEO):

Social media sites that rely on content creators to post original content also oblige those creators to compete to have their content seen. They tacitly encourage content creators to use methods that increase visibility (titles, tags, subjects, trending topics, cover photos etc.). A popular content type on YouTube is search engine optimization (SEO) videos for content creators.

Since content can be monetized by creators to generate revenue from advertisements, the new career path of "YouTuber" has emerged. Alongside of this is the emergence of videos created by YouTubers *for* YouTubers, videos that describe the best techniques to increase views on the platform. People creating SEO videos attempt to decode YouTube search and discovery algorithms to help content creators leverage viewers and gain popularity.

Most SEO videos discuss the metrics used by YouTube to recommend content. Because these videos are made for content creators, they are mostly concerned with the explicit metrics of audience engagement that creators have the most control over. In this way, recommendation algorithms heavily influence the types of content produced and the packaging of content.

Creator Insider and *YouTube Creators [Creator Academy]* are channels ran by YouTube employees describing the explicit metrics that recommendation algorithms use as input so creators can optimize content. These metrics are likes, comments, shares, and video descriptions (V12; V14; Gielen, 2017). YouTube tells content creators these metrics are consider as "engagement" and recommendation algorithms consequently recommend on this basis. Videos optimized for these metrics are said to increase traffic, a term that refers to the number of users engaging with content. Independent YouTube SEO consultant channels *Brian G Johnson TV*, *Brian Dean*, and *Roberto Blake* instruct creators how optimize titles by front-loading keywords, manipulating the audience through hyper-specific calls to actions to increase commenting, using the correct amount of tags, striking thumbnail image design, video description text length, meta-tags containing trending words, and ideal video length (8-15minutes) (V19; V21; V31).

These messages have certainly reached creators. The end of 2016 was marked by a wave of content creators criticizing peers for optimizing videos for explicit metrics to better leverage audiences. *H3h3 Productions* criticized the emerging trend of pleas to like, comment, subscribe, disingenuous titles ("click-bait"), product giveaways, and misleading or sexualized thumbnails as manipulation of audience and algorithms resulting from optimization (V3). Gamer *jacksepticeye* claimed the explicit metrics algorithms "punish" content creators who do not use manipulative SEO tactics, thereby discouraging diverse or creative content (V5). Conservative political commentator *Steven Crowder* protested that the algorithms encourage empty buzzwords, fabricated drama and confirmation bias (V7). French vlogger *SQUEEZIE* echoed many YouTubers sentiments that these content optimization techniques were ultimately blunt tools attempting to unlock the black-boxed recommendation algorithm (V6).

This shows that the content being uploaded to YouTube is affected by creator assumptions of recommendation algorithm mechanics. Content creators believe that these metrics are privileged by algorithms and will result in more views, and therefore try to optimize content for the metrics. The functions of algorithms, or merely the perception of those functions, are reflected in uploaded content. This type of power conforms to Lash's definition of domination in a "post-hegemonic world" (Lash, 2007; Beer, 2009, p993). Content creators internalize the desires of the platform imparted upon recommendation algorithms and willingly attempt to conform. The post-hegemonic power of the platform acts from below the individual, rather than from outside or above the individual as in hegemonic power. The algorithmic prioritization, classification, association and filtering of cultural content by the platform encourages content creator to conform to types of content privileged by recommendation algorithms. The types of discourse that may exist on the platform are thus limited before their conception by the self-organization of content creators.

Implicit versus explicit metrics:

The revealing neural network article published by YouTube software engineers dampened the glorification of explicit metrics, leading to major members of the YouTube community discrediting their effectiveness. News and popular culture personality *Philip DeFranco*, who optimizes his content for explicit metrics through product giveaways and hyper-specific appeals for comments, disagreed with his peers. Despite DeFranco's videos regularly having excellent engagement they never appear in trending (V4). Videos began appearing refuting the weight of explicit engagement metrics. Entertainment, videogame and SEO specialist channel *The Game Theorists* says that recommendation has little to nothing to do with explicit engagement metrics, but rather with watch time and user retention over time (V8). Vlogger channel *PewDiePie* lampooned content creators' efforts to optimize for explicit metrics in his video "Can this video get 1 million dislikes?", saying that these efforts are nullified due to the secretive nature of YouTube algorithms (V9). In 2017 multiple SEO channels further built on the arbitrariness of explicit metrics to YouTube recommendation algorithms. *The Game Theorists* explains that the candidate generator neural network selects videos to be ranked largely based on the user's previous searches and watch time (V10). Audience-controlled explicit metrics such as likes suddenly appeared inconsequential.

After contact with YouTube software engineers, SEO specialist Derral Eves divulged the website's heavy reliance on user meta-data (V31). YouTube collects multiple points of data on videos' performance throughout their lifetime as well as user behaviour. These data points are combined in metadata sets to recommended content that, based on user behaviour, should keep users on-site for the longest possible period of time. Watch-time, CTR/impression and associations between categories of users' behaviours are the key metrics recommending content. These metrics even take into account how a viewer is watching a video. Although it is impossible to know whether a video that is playing in a web browser is actually being watched, audience interactions with the video host such as muting a video or scrolling back through a video to re-watch segments are taken as indications that an audience member is truly watching and engaged.

YouTube has misled content creators on the level of agency that their actions have in affecting algorithmic recommendation. The expectation that certain explicit metrics controlled by content creators and users are algorithmically privileged seems misguided when compared to the sheer amounts of meta-data mined by YouTube. Content is being produced with "the Algorithm" in mind, however content creators express their frustration with the black box. Key players on YouTube including *h3h3 Productions*, *jacksepticeye*, *PewDiePie* and *Philip DeFranco* all express irritation with the lack of communication from YouTube regarding metrics associated with recommendation, as well as the types of optimized content that result from the believed state of these metrics. *Jacksepticeye* and Ethan Klein of *h3h3* told millions of viewers in separate videos on the topic that greater transparency is necessary, that the YouTube recommendation "algorithm punishes users" (V5), with Ethan pleading "Just tell us what you are doing!" (V3). These are complaints directed at the algorithmic black box.

For YouTube, implicit metrics gathered via thorough surveillance of the granular behaviours of users are far more important than explicit indications of audience desires. Recommendation algorithms affect audience and YouTuber behaviour as well as video content. The vast amount of implicit data gathered from user behaviour creates quantifiable individuals better targeted for advertising and therefore a commodity that is more valuable to advertisers (Pasquale, 2015, p4; Mager, 2012, p771). Content creators internalize the economic interests of YouTube, while users are surveyed for capital gain. The variety of content that emerges from the process also becomes relatively standardized.

Recommendation standardizing content:

In attempting to optimize content from the recommendation algorithms, content creators conform to types of content that appear more popular than others. *H3h3 Productions* remarks that algorithmic privileging of longer videos to maximize watch-time, makes painstaking animation videos obsolete **(**V2**)**. Nigahiga's comedy song "Getting views on YouTube" poked fun at content creators who conform to trending video themes such as apology videos, YouTube community drama, un-boxings, fidget spinners and slime (V18). The channel encourages YouTubers, tongue in cheek, to create content for the "lowest common denominator", and to "play ball" with YouTube to ensure recommendation and watch-time.

This demonstrates the capacity of recommendation algorithms to act as cultural gatekeepers. The influence of recommendation algorithms on the content that creators decide to publish results in mass production of videos that are predicted to attain greatest watch-time. Mass production motivated by algorithm functions leads to a standardization of content that is perceived to be appealing or popular (Dormehl, L, 2014, p155).

3. "Freshness"

Youtubers were at the front of mainstream media sources in 2018 due to mounting mental health concerns among the creator community. Mental health issues, particularly multiple YouTubers suffering from "burnout", were featured in international news platforms such as *The Atlantic*, *CBC News*, *Forbes*, *Global News*, *The Guardian*, *NPR*, *Variety*, and *Vice*.

Occupational burnout, or burnout, is a condition of "physical, emotional, mental exhaustion…most often observed in professionals who work in service-oriented vocations (e.g., social workers, teachers, correctional officers) and experience chronic high levels of stress" (American Psychological Association, 2018). Content creators claimed that their mental health was suffering largely due to unreasonable publishing schedules that demanded 2-4 videos per week. As an intermediary platform, YouTube officially imposes no publishing obligations on content creators; creators may publish what they like when they like so long as the content does not breach community guidelines. However, creators claimed that they in fact do feel an obligation to post frequently due to YouTube recommendation algorithms privileging new or "fresh" content.

The Freshness Input and Content Creators:

Algorithms produce desired output through training using past data sets. Because training data sets are finite, over time neural networks may recognize and retain test data sets, becoming biased to past data and therefore have difficulty completing a desired output sequence when faced with new data. "Freshness" is an input category of YouTube recommendation algorithms in both candidate generation and ranking processes (Covington, Adams, Sargin, 2016). The age of a video (how long the video has been online) and the performance of the video since its publication is included in machine learning to ensure algorithms recommended new content that would otherwise be largely ignored. Freshness is balanced with the past actions of the user to ensure that the new content remains user relevant. Google software engineers regard freshness input as valuable because it:

1. increases watch time on recently uploaded videos.

2. provides varied impressions to new users, whose click-through/failed click-through will inform future recommendations; and
3. encourages viral sharing of content.

Preference of freshness in recommendation combined with the effect of subscriber burn encourages content creators to publish standardized content often in a genre niche (V10). If users or subscribers do not click through a video impression multiple days in a row, perhaps because the content is not pertinent or interesting to the user, the content will no longer be recommended. Therefore, content creators publishing bi-weekly or even daily risk dramatic losses in views if they create diverse content that may only appeal to a segment of their recent viewers. *YouTube Creators [Creator Academy]*, a resource made by YouTube to instruct creators how to best optimize content for the platform, confirmed these findings by encouraging creators to post often and commit to a niche to be regularly recommended (V16).

The Game Theorists notes the rapid growth of diverse channels in 2016 and attributes it to their identical publishing schedules (V8). All channels were publishing long videos daily (8-15 minutes) while remaining in a particular genre niche. Users return daily to consume the content and the channel amasses greater watch-time. Because recommendation is based on how likely and often a user is to watch for the longest period, these channels receive a substantial boost in recommendation.

The high content production schedule encouraged by recommendation algorithms became a talking point for mainstream media after *Jackspeticeye* and *ElleOfTheMills* public statements that they were experiencing mental health crises. Both refer to their isolating production schedules, *Jackspeticeye* explicitly referring to the monotony of producing niche content daily as a mental health trigger (V33, V34). The topic of mental health among YouTube creators trended for the following months, even being identified by YouTube as a notable moment of 2018 in the platform's annual review video (V35). While these creators began the North American discussion, international YouTubers had already discussed the consequences of daily posting and content niches. In July 2017, French blogger and gamer *SQUEEZIE* affirms that the high content production schedule privileged by recommendation algorithms had led to him forcing himself to publish an average of four videos per week (V11). *SQUEEZIE* says that the video analytics available to content creators lead to an unhealthy obsession with video performance statistics and subscriber counts, and the intense schedule resulted in poorer quality content that he felt an obligation to produce.

In a meta-commentary on the 2018 content creator mental illness trend, YouTube personality *boogie2988* blamed the phenomenon on the weighting of freshness by recommendation algorithms, stating "we [YouTube content creators] feel enslaved by the YouTube algorithm" (V28). He feels that the way the algorithms are designed to function demands creators to produce content on a weekly or even daily schedule and that taking time off from content production risks losing valuable leverage of their channel's audience. According to *boogie2988*, the high content production may in fact lead to less audience engagement, because keeping up with the schedule leads to poorer quality, homogenous, "rushed" content, resulting is poor audience retention and thus poorer recommendation. YouTube comedy bloggers *nigahiga*'s spoof video "How to get Views on YouTube!" hints that due to the recommendation algorithms, creating fulfilling content is cursory to frequent publishing of longer videos on trending topics (V18).

YouTube SEO specialist channel *Roberto Blake* accounts for the emergence of daily vlogs and burnout as a result of the freshness input:

> *"… if you're wondering why YouTube mental health has been coming up as a topic a lot it's because of the changes in the algorithm and this cycle of attention and over-optimizing … YouTubers feel like they're on a constant treadmill to keep making content over and over that's why people are trying to go daily … if you aren't making enough content then you might not be in the last 100 videos someone watched which means when you do upload YouTube may not serve that content to people."*
> *- (V29)*

YouTube software engineers responded to these concerns, claiming that YouTubers taking "breaks" from publishing content would "not kill their channels" (V20). They argue that so long as subscribers remain loyal and consume content when published, engagement and watch-time will remain similar. Likewise, if one video published does not perform well, this will not "greatly" affect future content as each video is "somewhat" recommended on its own merits.

YouTube further responded to claims of recommendation algorithm-induced burnout. *YouTube Creators [Creator Academy]* hosted by YouTuber and graduate in clinical psychology Kati Morgan to discuss recognizing and preventing the main causes of burnout (V23). Morgan identified five reasons for burnout; pressure to create, over-monitoring video metrics, the extended hours of internet operation, audience criticism, and the constantly changing nature of digital environments. The emphasis is on the perceptions of the creator towards the algorithm, their audience, YouTube, and the internet. Morgan frames mental health crises as induced by an individual's desire to succeed on a platform by maintaining a production schedule and content types that conform to recommendation algorithms.

YouTube thereby confirms that posting niche content regularly is a good tactic to leverage recommendation algorithms. Simultaneously, YouTube confirms the existence of creator burnout and rejects that taking breaks from production will necessarily harm channels. Considering previous problems with optimization of subscription feeds, it seems unlikely that all channels could expect regular levels of engagement after a content drought merely due to loyal subscribers. YouTube recognizes the phenomenon of burnout yet distances the platform from any responsibility; detailing the functions of "freshness" as a key measure in recommendations, while conversely telling people suffering from mental illness due to high content production schedules that it is due to their own personal perception of "the algorithm". This contradictory approach avoids culpability.

It is worth noting cynical responses to the wave of mental health videos that emerged after the topic gained traction on YouTube and in the mainstream media. Previous empirical findings show that YouTubers attempt to manipulate freshness and trending metrics by creating content addressing current events and trending controversies (Rieder et al, 2018, p60). YouTube's *Creator Insider* team confirms that video concerning a certain trend will be recommended during the trend's period of popularity (e.g. fidget spinners, slime) (V13). Comedy, news, and opinion channel *Memology 101* accused content creators of manipulating recommendation algorithms for greater watch-time by commenting on a trending topic, in this case mental health/burnout (V30). This is an example of manipulation of the freshness metric by creating content on current issues, genuine or otherwise, when content creator burnout was a dominant topic on the platform.

However, manipulation is also applicable to YouTubers creating videos critical of a trend. *Memology 101*'s video could be considered a controversial reaction as well as an attempt to manipulate users and recommendation algorithms. Ultimately the tactic failed for *Memology 101* as his video was poorly received, and he later commented "I am bleeding subs after this video…". The tactic conforms with recommendation preference for current events, trends, and fresh content (Rieder et al, 2018, p63).

4. Content suppression:

An important recent input of YouTube recommendation algorithms is the classification of video content. Like the classification of a film based on its content, YouTube classifies videos against the anticipated age of their audience. Algorithms then recommend or suppress content depending on the age and consumption habits of the user. This is a value judgment by YouTube and enforced in their recommendation algorithms.

The rating system appears to have been a reaction to the major loss of advertising Google suffered in 2017, which users of the platform call the "apocalypse". The apocalypse occurred when international companies such as Pepsi, Walmart, and AT&T removed advertising from YouTube due to their publicity playing on monetized accounts that promoted neo-Nazi and Islamic State propaganda (Burgess, Green, 2018, p149; Manilève, 2018, p146). In an effort to maintain paid promotions and ad revenue YouTube put into place stricter rules concerning the amount of viewing hours and subscribers a channel requires before accessing monetization (Gillespie, 2018, p70). This hurdle is a test by YouTube and reveals how the platform determines the quality of content. A channel not respecting community guidelines or publishing content that is distasteful to some viewers would not be assumed capable of reaching this amount of watch time or subscriptions without community strikes having already eliminated the account (Manilève, 2018, p147). In addition, content that YouTube determines to be controversial or sensitive could no longer be monetized, including content depicting war, natural disasters, terrorist attacks, school shootings, tragedies etc.

YouTube creates general categories to determine whether certain types of content are appropriate for certain audiences. Although a certain video depicting violence or containing vulgar language may not breach the site's community guidelines, YouTube categorizes videos to avoid recommending these types of content to younger viewers. These categories are similar to film age restriction ratings. Four rating categories exist (Karlaplan, 2018). When advertisers pay to publicize on YouTube, they may select the rating types of content they wish to advertise against, generally dictated by their target audience. They may also select the types of sensitive content they do not wish to advertise against. Unlike content creators, advertisers have greater access to the black box of recommendation algorithms because YouTube allows them to selectively buy their audience. This demonstrates that advertisers have greater power on the platform (Gillespie, 2014, p185).

Ratings:	**Sensitive content:**
• General audiences • Parental guidance • Teen and older • Mature	• Tragedy • Sensitive social issues • Profanity • Sexually suggestive • Shocking

Table 4. YouTube content rating categories

Content rating became a talking point for YouTubers in 2018 when multiple content creators noticed that demonetized videos were not preforming as well due to being under-recommended. The assumption was that YouTube recommendation algorithms preference monetized content over non-monetized content because the company earned a portion of each monetized video's advertising. The theory gained so much traction that YouTube, via Twitter, *Creator Insider* and *YouTube Creators [Creator Academy]*, responded to the concerns (Team YouTube, 2018; V20; V36). According to YouTube, demonetized videos may be recommended less because of their content.

YouTube collects a portion of ad revenue when advertisements are played on a video.
To maintain business partnerships with advertisers, YouTube identifies certain types of content as non-advertiser friendly or sensitive and will not run ads on those videos. A monetized video is video content that can play advertisements and generate ad revenue, and a demonetized video is video content that cannot play advertisements nor generate ad revenue.

YouTube algorithms are programmed to recognize video ratings based on the categorization of content as sensitive as well as the categorization of the user's age before making a recommendation. The monetization status of these videos is importantly related to the rating of the content. A video identified as containing sensitive content will not be recommended to users identified non-mature, and due to the content being identified as sensitive, may not be able to be monetized. While the identification of sensitive content affects monetization and recommendation to different audiences, monetization does not directly inform recommendation.

Philip DeFranco claims YouTube recommendation algorithms suppress his content due to its categorization as not advertiser friendly (V25). Due to machine learning, recommendation algorithms are pre-emptively suppressing his content because his channel is categorized as publishing sensitive content:

> *"Several of our videos were suppressed. Tons of comments saying, 'The video's not popping up where it normally does. What's the deal?'. Next morning, the videos have around three hundred to four hundred fifty thousand less views than the average videos normally have. But it doesn't make sense to people that watch my show on a regular basis that I'm not popping up on the homepage, recommended, watch next."*
> *- Philip DeFranco (V25)*

This appears to conform to Google's tendency to use machine learning as "a general-purpose solution to nearly all learning problems" (Covington, Adams, Sargin, 2016, p191). *DeFranco* goes further in a later video, blaming the algorithm for a 15% drop in viewers landing on his videos from the home page or side bar, the two most recommended locations on YouTube (V32). This drop appears to be directly related to his report on the bullying of a Syrian refugee, which had been deemed "controversial" and "violent" content. In said video, *DeFranco* had been explicitly condemning the violence and sharing a message of general acceptance.

This controversy aligns well with two experiments conducted in 2017 and 2018. In two separate experiments to reverse-engineer recommendation algorithm content suppression, YouTuber *Sealow* and *Karlaplan* showed that YouTube restricts videos from appearing in recommended due to language and adult themes (Karaplan, 2018, p10). YouTube assumes the age of the user by consumed content, and limits recommendation of videos rated as "Mature" or "Teen or over".

These two studies explain *DeFranco*'s complaint that his videos deemed as containing "controversial" and "violent" content were supressed, despite *DeFranco*'s comments critiquing the violence.

While the sheer quantity of meta-data gathered as input for recommendation algorithms is impressive, programmers are still incapable of designing algorithms that can watch, assess, and make value-judgements of the classification of audio-visual content. Rather, the algorithms are designed to identify/recognise words (spoken or text), sounds and images decided upon by programmers to be indications of sensitive content. Thus, recommendation algorithms rely on keywords defined as "sensitive content" by the platform that are found in tags, titles, and closed captioning. YouTube is enlisting machine learning to make value judgments concerning the sensitive nature of content and the right audience for classified content. *Sealow* and *Karlaplan's* experiments claim that this is a blunt tool when rating the content of a video, with examples of queer awareness videos, content related to the #MeToo movement, and suicide-prevention videos being rated mature and consequently suppressed. However, this method does not necessary reveal YouTube's position on sexual harassment or suicide prevention as much as it reveals the incapacity of engineers to create algorithms that reliably process nuance.

Classification made entirely on keywords is a form of protection for YouTube. Due to the sheer quantity of videos being published, YouTube prefers to algorithmically suppress content regardless of its substance because doing otherwise would put the company at risk of losing advertising revenue. It is more important that a video containing truly sensitive content (e.g. gore, inciting violence) be algorithmically suppressed, even if that is at the cost of 1,000 videos that, upon human review, prove not to be sensitive. The arbitrariness of inaccurate or unfair suppression by algorithms is a cost the platform is willing to accept to protect capital.

A controversy that demonstrates the bluntness of algorithmic rating to accomplish such a task is YouTuber Logan Paul's suicide forest video. In 2018 *Logan Paul Vlogs* uploaded a demonetized video that contained images of a corpse suspended from a noose. The video spent a short period recommended on the YouTube home page and to *Logan Paul Vlogs* subscribers before being taken off the site. When asked for comment in an interview with vlogger *CaseyNeistat,* a

YouTube executive admitted that the video was recommended because it was preforming well, “there were a lot of searches for it all around the world and on YouTube, and so it ended [on the homepage]" (V22). This conforms with previous findings that popular Google search queries act as an input for YouTube recommendation algorithms (Rieder, et al., 2018).

The disturbing content, which was later condemned by the platform, slipped easily past content classification and became valuable input for recommendation algorithms to promote to *Logan Paul Vlogs*’ largely child audience as well as non-subscribers. The executive’s explanation relies on the perception of algorithms as functioning objectively and the difficulty of curating and moderating large amounts of content. In doing so YouTube rejects responsibility for the controversy generated by sensitive content being automatically recommended by algorithms. The rejection of responsibility is necessary because the design of the algorithms was being conflated with the actions of YouTube. When users blamed YouTube executives for the disturbing content being promoted, the executives point to the complexity of algorithmic recommendation rather than taking direct responsibility. This feeds into the concept of the Algorithm, attributing blame to non-human agents (algorithms) rather than the human agents (executives, programmers) that commission, design, and upkeep the non-human agents. This attributes blame to algorithms and shows how audiences critiquing YouTube appear to overestimate the agency of larger corporations to reliably guide recommendation.

YouTube’s rating system is another input considered to better funnel content towards or away from users. It is another example of categorization of content and users to avoid controversy and thus maintain the platform’s financial well-being. YouTube is concerned with keeping user watch-time high, but only if they can also harness users’ attention to create profit. If watch-time ceases to create revenue, users cease to be the platform’s capital (Gillespie, 2018, p179). YouTube is willing to do so even at the risk of suppressing content that the community does not deem sensitive.

Discussion:

Personal Data and Behavioural Data:

The findings of this study titled “Big Data Collection” and “Behavioural Data” confirm previously published works in the literature review regarding the controlling nature of algorithms, the technical and economic motivations of companies to use algorithms, and the subsequent critique of these companies’ economic motivations to use these algorithms.

The findings of this study that are related to *watch-time* and *subscriber burn* show that YouTube is concerned with collecting data for economic reasons. More specifically, the focus on watch-time demonstrates that YouTube prefers using behavioural data over users’ explicitly expressed preferences. YouTube is primarily concerned with keeping users on the site for the longest period possible so that the company can increase revenue from paid advertisements as well as gather greater behavioural information from people spending time on the platform. User-controlled metrics are tools offered to users to actively indicate their approval or disapproval of content measures and are considered by most users as active exercises of user agency. Them being ignored confirms that they are insignificant to YouTube in comparison to non-explicit metrics such as the amount of time being spent on the site (i.e. watch-time). The platform is primarily motivated by economic reasons and proves that the design of their data collection disregards user-controlled metrics of satisfaction such as liking or sharing.

The second finding in part one is subscriber burn. The existence of subscriber burn demonstrates that YouTube constructs a personal profile of each user from the data metrics collected to better predict how a user may react to some kinds of video content, and ultimately recommend content algorithmically that YouTube believes will increase watch-time. This is demonstrated by YouTube ignoring users’ explicit desire to receive notifications from YouTube when creators that they have subscribed to publish content. YouTube algorithms are designed to recommend other types of content predicted to increase watch-time, ignoring content that a user has subscribed to if the user is identified as having shown any previous hesitance or has failed to consume subscribed content.

Watch-time and subscriber burn are both products of the same objective, to maximize profits by keeping users on YouTube for as long as possible. These two functions of recommendation algorithms ignore explicit metrics that users may provide, instead preferencing implicit behavioural data of how the user acts. YouTube paternalistically preferences this data because they believe it will lead to greater audience retention regardless of how the audience claims to want to act on the platform.

These two findings also indicate general categories that YouTube uses to organize the user data that they collect. Using the findings of this study, it is useful to conceptualize YouTube user data collection as being separated into two related but distinct groups; *personal data* and *behavioural data*.

Personal Data:

Personal data refers to the discreet demographic data provided by a user when they use the website. Some of this data is provided by the user when they create an account (e.g. name, DOB, country, gender) or, in the case of YouTube, can simply be carried over from previous Google accounts. This pales in comparison to the amount of data that can be mined through the use of IP addresses of computers being used, cookies of websites that the IP address has previously visited, and data garnered by Google after a long period of analysing existing users that have no YouTube account. These types of personal data are much more valuable to the company because they are considered more objective than any individual self-report of location, name or gender.

Personal data collection is concerned with creating categorized online identities for the user and subsequently align this identity with others that are identified as belonging to similar groups. YouTube is categorizing users through some user-submitted data, but mostly data captured from user behaviour. YouTube does this to construct an identity for any given user and associate that constructed identity to other users that have also been categorized as belong to a similar/identical identity. For example, if I have been categorized as a 32-year-old white male living on the East Coast of North America, it is generally expected that I will be interested in similar things to other users belonging to the same category. This is based in what Gillespie calls a "conservative logic" that similar people are expected to act in similar ways (recidivism, guilt by association, genetics, etc.) (Gillespie, 2018, p109-110). Categorization fuelled by personal data collection and subsequent association that is responsible for a large part of YouTube recommendation. These findings conform to previous literature concerned with the controlling nature of algorithms, as well as literature critiquing the economics motivations of platforms deploying algorithms. When gathering data and designing recommendation algorithms, YouTube is more concerned with categorizing users as a part of a constructed group, rather than users' individual desires or self-report.

Behavioural data:

Behavioural data is the data collected on the minute actions of a user. Examples of behavioural data on YouTube include skipping or repeating sections of a video, the type of device used to access the platform, the types of videos users will return to and how often, search terms etc. Behavioural data is related to personal data collection, in that its goal is to better inform YouTube's constructed categories of user identities. Trends that are identified in behavioural data are assumed to be consistent within entire categories. This type of data acts as an empirical support for YouTube's constructed user categories and assumptions that certain categories of person behave in a similar way. Like with personal data, the goal is to better know, predict and influence individuals to stay on the platform.

These two types of data collection conform to the literature critiquing the economic motivations of companies, as well as literature suggesting that big-data collection by large tech companies is evidence of emergence into a new form of economic existence ("surveillance capitalism") that is concerned with modifying human behaviour to ensure greater predictive power and therefore greater profits. These findings exhibit the abstractions of the world that big data collection and algorithms are capable of processing, they conform to the economic motivations of YouTube, and they ignore the consequences for human agency online by discounting the consequences of creating abstract categories.

Algorithms affecting content creators as an example "post-hegemonic" domination:

The standardization of content on YouTube and the mental health/burnout movement among creators are two findings that conform to the literature as instances of post-hegemonic power. Content standardization and burnout both occur as results of the actions of content creators on the platform; content standardization was the result of creators attempting to optimize their videos for what was popularly considered to be the best metrics for better recommendation by YouTube algorithms; creators claimed that burnout was the result of creators attempting to maintain a publishing schedule that was popularly considered to be ideal for recommendation by YouTube algorithms. In both cases the popular perceptions of how YouTube recommendation algorithms function is reflected in the content being published to the platform as well as the experience of content creators that publish on the platform. Content creators act in this way to gain success on the platform, however their perception of success and how to achieve success is influenced by YouTube's economic desires. Content creators conform to unwritten rules about how their content should be published because they believe that this will result in improved algorithmic recommendation. This type of behaviour can be used to support the theoretical framework of Lash and Beer.

The first example of post-hegemonic power from the findings of this research refers to content standardization. There is a discourse in the YouTube creator space concerning the idea that recommendation algorithms are responsible for a standardization of content. This is evidenced by the number of YouTubers discussing other creators publishing videos that attempt to manipulate YouTube recommendation algorithms. Examples include watch-time's effect on animation videos and standardized formats of videos that implored viewers to engage with the content using likes and subscriptions.

First, the preference of total watch-time generated by a video instead of audience engagement or satisfaction with the quality of a video leads to poor recommendation of labour-intensive content. Watch-time encourages content creators to produce videos between 8 and 15 minutes in length, which has become a common format for content creators. A recurring example from the findings critiqued the decision to train recommendation algorithms to preference longer videos, specifically in the case of animation content. Digital animation is an intensive process that requires many hours to create content of a few minutes. Due to YouTube preference of watch-time, animator content was less recommended and animation content creators were less likely to generate revenue from the platform.

Second, many creators in the study highlighted and often mocked a movement on the platform of creators begging viewers to explicitly engage with their videos so that they may be better recommended on the platform. The most common jest was creators asking viewers to "like, comment and subscribe", three types of engagement that creators believed would act as input for recommendation algorithms and lead to content being more recommended. Despite these relevancy metrics being shown to have very little influence on recommendation algorithms, creators felt the need to conform to their fellow creators' pleas for engagement, leading to a standardized and eventually mocked video format.

These examples demonstrate that the functions of recommendation algorithms, or at very least the perception of those functions, has led to standardized changes in the behaviour of content creators and what types of content are being created. The design of recommendation algorithms modifies the behaviour of users by delegating specific responsibilities to creators to succeed on the platform. This demonstrates the influential nature of platforms and their algorithms and can be considered as in line with Lash and Beer's theory of post-hegemonic domination.

In Lash's conception of post-hegemonic domination, the economic desires of the YouTube platform are reflected in the functions of recommendation algorithms and content creators internalize those economic desires by attempting to create recommendable content. The influencing power of the platform acts via algorithms from below the individual rather than from outside or above the individual as in hegemonic power. Specifically, controlling the types of discourse people may choose to engage with by blocking and channelling content, thereby excluding sensitive topics from the sphere of discourse rather than trying to coerce or convince compliance after a certain discourse is communicated.

The second example of post-hegemonic power from the findings refers to the variable metric developed by YouTube called “Freshness”. This metric is an input for recommendation algorithms, leading to the perception that consistently publishing new content would be lead to greater recommendation by algorithms. This led to multiple creators claiming that they felt an obligation to uphold an unmanageable production schedule despite YouTube imposing no official no publishing schedule obligations. The weight of this perceived production schedule negatively affected creators’ mental health.

The freshness metric is evidence that multiple creators on the YouTube platform felt pressure to act in certain ways due to their perception of recommendation algorithms. Creators felt the need to publish standardized content often in a genre niche, with *YouTube Creators [Creator Academy]* actively telling creators that this will lead to regular recommendation. In doing so, they experienced a feeling of lack of self-agency due to their desire to succeed on the platform, eventually leading to mental health crises. This reality of the freshness metric conforms to the literature that is critical of the controlling nature of recommendation algorithms. The perception of the mechanisms of algorithms directly affects the well-being of creators attempting to succeed on the platform.

Lash and Beer’s theoretical framework explains well the influence of YouTube recommendation algorithms and motivations behind that influence in these cases of creator mental health. The functions of algorithms, or merely the perception of those functions, are reflected in content uploaded to YouTube. This type of power conforms to Lash’s definition of post-hegemonic domination. Content creators internalize the desires of the platform imparted upon recommendation algorithms and willingly attempt to conform. More specifically; the actions of content creators that are attempting to succeed on the YouTube platform can be theorized as a reflection of the economic motivations of YouTube and therefore the functions of YouTube recommendation algorithms. YouTube content creators, whether conscious of the fact or not, are conduits for the motivations of YouTube, only capable of creating art that conforms to the technical functions of recommendation algorithms and the overall economic motivations of the company.

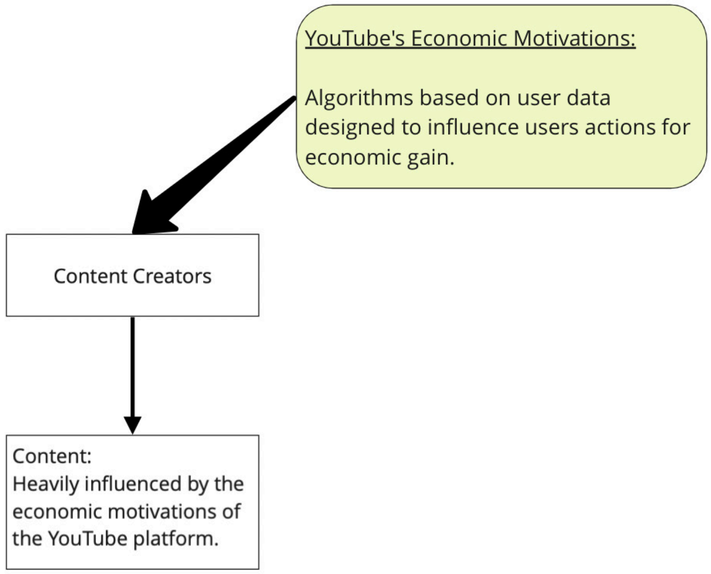

Figure 1. ***Theoretical framework of Lash and Beer applied to YouTube content creation:*** *The content being created by a YouTuber is influenced by the YouTube platform. The content resembles what the content creator is experiencing, a* top-down *force that guides action and limits agency.*

Further, content creators experience sentiments of stress and depression due to their conception of how YouTube recommendation algorithms function. These sentiments are the result of an impression of YouTube algorithms that favour reliable high-content production. The actions or the stress due to inaction of content creators is induced by their desire to conform to recommendation algorithms on the platform. Said otherwise; the actions or the stress due to inaction of content creators is induced by their conception of the economic motivations of YouTube.

On explicit users, tinkerers and critical content:

The findings of standardization and mental health movements align with Lash and Beer's theoretical framework that YouTube and their algorithms influence content creators and the content that is being produced. However, this type of framework was not able to account for multiple occurrences of everyday yet significant agency identified throughout the study. Van Dijck and Gillespie endorse many of the same views as Lash and Beer, specifically the coercive possibilities of recommendation algorithms when deployed by economically driven companies. However, their theoretical framework considers the users of platforms as parts of a network of stakeholders that are influenced by algorithms while also playing an important role in producing algorithms.

Van Dijck's distinction between implicit (passive) users and explicit (active) users is valuable to better understand the diversity of the findings. Explicit users educate themselves on technology and seriously consider the values and goals of platforms to make an informed decision to either resist or conform to algorithms depending on their personal values. These users identify something as a problem and form a strategy to solve that problem using the technics available in their environment. Cases of explicit users are present in the findings and can be coded into a typology of users to build upon this implicit/explicit distinction. Of the 32 cases studied, the creators fall into three different categories of explicit YouTube content creators: *Tinkerers*, *Entertainment/commentary (EC)*, and *YouTube affiliated*.

Tinkerers:

Tinkerers are similar to what Frantz would call hobbyists. Individuals and groups using informal self-education methods to learn and teach within a community. Tinkerers identified in the study are concerned with the functions of YouTube algorithms, the motivations for YouTube to create those algorithms, and the effects that those algorithms have on the YouTube environment. Tinkerers from the study include creators such as *The Game Theorists*, *Brian Dean*, *Brian G Johnson TV*, *Nerd City*, *Robert Blake*, and *Derral Eves*. These are creators that show a thorough knowledge of the YouTube platform and recommendation algorithms in general. This is a knowledge of algorithms, the technical functions of the platform and the motivations of YouTube. These tinkerer creators publish content to inform users and other content creators of how the YouTube platform functions and suggest how those functions affect them. For users, this means gaining a better understanding of how personal and behavioural data is being monetized by platforms like YouTube. For content creators, this means explaining how they can better achieve monetary success on the platform.

Tinkerers in the study are researching and experimenting with the YouTube platform to produce informative content for users. This type of content is as concerned with YouTube recommendation algorithms as it is with the other stakeholders involved in recommendation. The content analyses, developments, and revelations happening in the technological world of YouTube and the corporate world of Google. Tinkerers know that to understand recommendation they must understand the functions of companies producing algorithms (i.e. how companies produce profit through advertising revenue, what kinds of topics trend, why…).

YouTube tinkerer content can be accessed by any user. However, because the topics that they cover are narrowly concerned with the YouTube environment, this type of content is principally made for fellow content creators. Tinkers are working to make black-boxed technology transparent to fellow creators in a collaborative effort to improve their fellow creators' YouTube experience. Many tinkerers can and *do* profit from their YouTube content. The majority of those found in the study appear to also be motivated by a desire to inform fellow content creators about the nefarious functions of YouTube algorithms. These are creators that believe to have erroneously experienced de-monetization, suppression, restriction or filtering of their videos due to YouTube recommendation algorithms. These tinker videos are as informative as they are cautionary. They act as a warning to future creators on how to produce content that will preform well as input for recommendation algorithms. At the same time, these videos inform users to be aware of the functions of YouTube and how to "trick" recommendation algorithms.

Tinkerers appear to be neutral in their assessment of YouTube algorithms rather than moralizing the process. These creators revel in the process of experimenting with YouTube algorithms, testing the limits of their functions and previous conceptions of their purposes. Even though they might advertise "hacks" or "tricks" to "hoodwink" YouTube algorithms, these seem to be techniques to make their content more attractive to audiences. This exaggeration is itself an attempt to manipulate algorithms and users by creating a clickable-titles for better recommendation. Contrarily, information about YouTube recommendation communicated by tinkerers was most often moralized by entertainment/commentary (EC) creators.

Entertainment/commentary:

Entertainment/commentary (EC) creators are similar to tinkerers in that they are interested in the functions of YouTube and they produce content related to this interest. EC creators differ from tinkerers because although there are cases of experimentation with YouTube algorithms in the study, these creators more often share the findings of tinkerers to their large audiences. EC creators from the study include *Jacksepticeye*, *H3H3 Productions*, *Philip DeFranco*, *SQUEEZIE*, *Steven Crowder*, *Pewdiepie*, *Casey Neistat*, *Boogie2988*, and *Memology 101*. EC creators act like mega-phones for the findings of the tinkerer content that they consume. They often compile past and new information regarding YouTube and YouTube algorithms to better discuss and inform their own experiences on the platform. EC content is more trend-based and less evergreen than tinkerer content. EC creator content is affected greater by trending topics than tinkerer content; EC creators follow trends and produce content relating to trends, whereas tinkerers are more often reflectively toying with the functions hidden behind those trends.

EC creator content is targeted towards implicit and explicit users that are not tinkerers. When an EC creator publishes a summary and commentary of tinkerer content regarding YouTube recommendation their large fanbase may often cause a backlash towards YouTube. In this way, tinkerers somewhat rely on EC creators if ever they want their analyses of YouTube recommendation to reach users that do not create content for the platform.

EC creators exist on the platform to make content so that they may produce profit, and critical content that they create is often motivated by their own frustrating experiences with the YouTube platform. EC creators appear to have a high consumption of tinkerer content because the assessments of tinkerers are so often re-broadcasted by EC creators. In this way, EC creators are *the* target audience for tinkerer content because they are personally invested in taking advantage of recommendation.

EC creators are explicit (active) users because they are attempting to educate themselves on the functions of recommendation to improve their own standing as a content creator. These users generally produce types of content that are much more diverse than tinkerers, and therefore create a more diverse audience. A YouTube algorithm tinkerer will produce content concerning a recent presentation by a YouTube representative, an academic article on Google AI learning or some tips learned from industry professionals at a weekend retreat. This is niche content made for people who wish to create content for the platform. The EC creators will consume this type of content to better leverage YouTube recommendation in their favour in the future. This is a type of content that is made for EC creators and therefore not a type of content that a casual or implicit user (inactive) would consume.

When EC creators broadcast their frustrations with the YouTube platform and its algorithms they are informed by tinkerer content. EC creators act as a somewhat distorting megaphone for the findings of tinkerers to a much greater inactive audience. EC creators are taking part in a collaborative community of users co-educating themselves to better understand black-boxed information.

YouTube affiliated:

The third category of content creator identified in the study can be described as YouTube-affiliated. These creators are official employees of YouTube that produce content for the platform to inform EC creators and tinkerers of how YouTube operates, new changes or additions to the platform, and how to use features of the platform. This type of content is made for explicit users of the site and would not be assumed to be interesting to an implicit public. Multiple videos used in the study were uploaded by *YouTube Creators [Creator Academy]*, a channel financed by YouTube that instructs creators how to navigate the platform and how to increase viewership. These videos provide information about recommendation and search, SEO, monetization, subscription, and general information about accessing metrics to optimize a channel. These platforms occasionally collaborate with successful non-YouTube affiliated creators to better reach and identify with audiences.

YouTube affiliated content often responds to trending topics or common user concerns that come up on the platform. Amidst a wave of concern surrounding creator burnout, *YouTube Creators [Creator Academy]* collaborated with EC creator *Kati Morton* to respond to accusations that YouTube's recommendation algorithms were a key cause of psychological illness amongst creators (V23). The collaboration was a response to a critique of YouTube, and the video gave general advice about how to avoid stress related with being a content creator, including not to look too much at analytics or compare your creating schedule to others.

This example shows that YouTube affiliated content creators play another important role: to protect the platform by obfuscating or denying liability in cases where recommendation algorithms are being critiqued. The existence of YouTube affiliated content creators demonstrates that YouTube is invested to a certain degree in accessing and influencing popular narratives that ripple through the site. Unlike official statements from top YouTube employees published as blog posts or in the news media, these videos are posted to the site just like any other content.

In the case of the Van Dijck and Gillespie theoretical framework, we are looking at an expanded diagram, where tinkerer content creators are in a network with YouTube affiliate and EC creators, as well as the general public. Rather than seeing the YouTube user or creator as being subordinate to YouTube economic motivations and algorithms, we should recognize the effects of different types of users on the landscape, and recognize agency (no matter how little), where it is found.

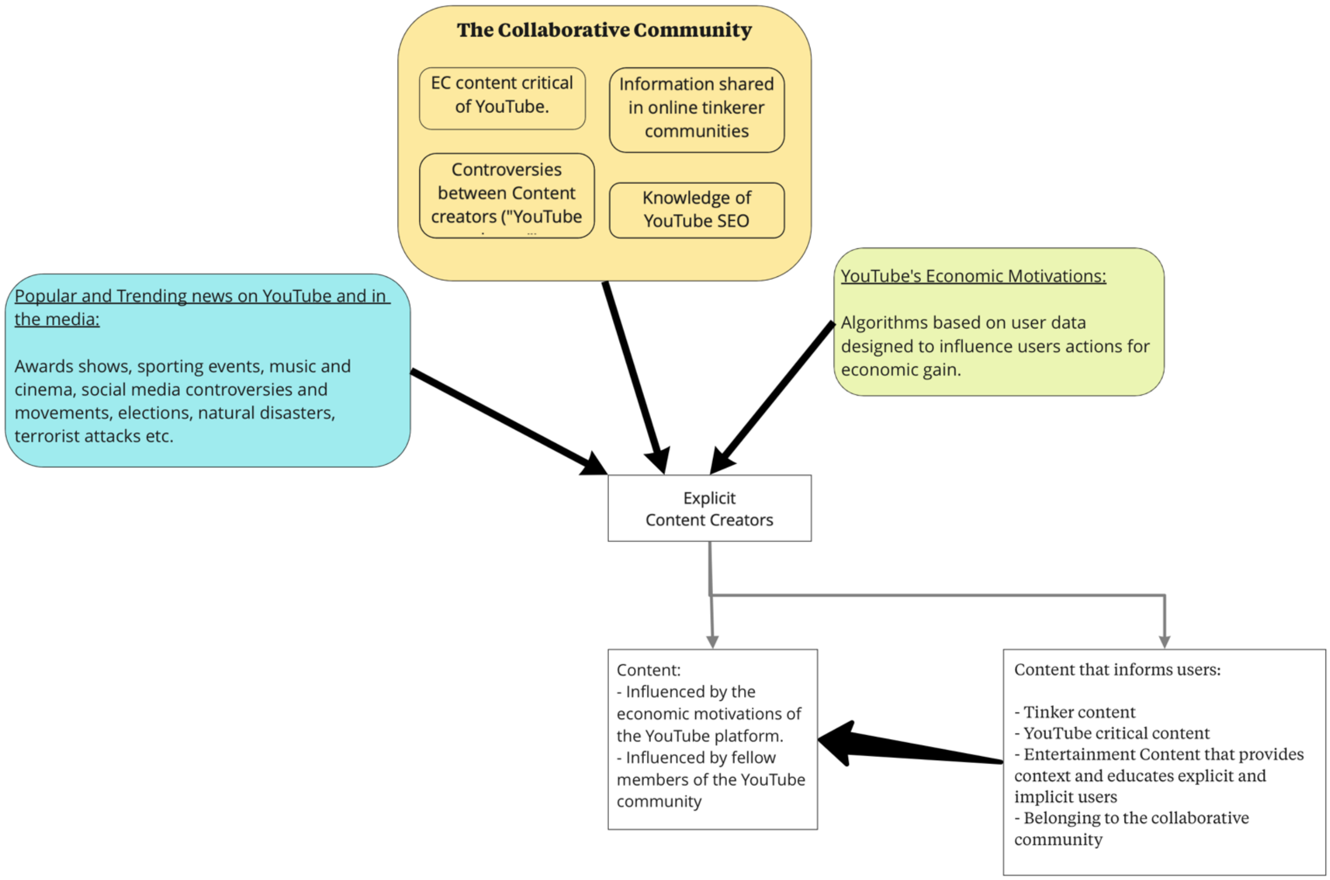

Figure 2. ***Theoretical framework of Van Dijck and Gillespie to YouTube content creation:*** *There are other types of content created by explicit users that exist within a collaborative community. YouTube content and YouTube recommendation exist within and are affected by this community. Explicit users are empowered through education and tinkerer content which affords agency.*

In summary, users creating tinkerer content on YouTube are what Van Dijck would consider to be explicit users. The explicit user is aware of the values and goals that platforms encode into algorithms and attempts to learn more about these systems to resist algorithmic herding (Van Dijck, 2013). This requires a knowledge of technology and the social, economic, and political motivations of platforms. Tinkers solve problems using the objects in their environment. In the case of tinkerer content creators, they are using knowledge garnered from experimentation and self-education to take advantage of recommendation algorithms. They are using this knowledge as a topic for content as well as a tool to take advantage of YouTube recommendation and reach other users. By publishing the information on the platform, tinkers contribute to an online community of creatives and consumers with shared concerns about user agency on YouTube.

EC creators consume tinkerer knowledge and apply it to their own content. EC creators apply technical knowledge of algorithms to their own experiences of controversy on the platform. The controversies identified in the study are primarily concerned with a perceived lack of user agency on YouTube. Therefore, EC creators amplify concerns about user agency, inform implicit users through non-technical explanations about algorithmic functions, and offer users a sense of communal being.

According to Beer, due to user familiarity with technologies like smartphones or Google search it has become difficult to critique or even to perceive algorithms, causing a "technological unconscious" (Beer, 2009). Tinkers and EC creators do extensive work on YouTube to reveal and appraise recommendation algorithms and the platforms' motivations. Like woman hobbyists tinkering with cars (Franz, 2005), tinkerer content creators are sharing knowledge within informal and disjointed communities using the tools available to them. Like users that modify video games (Wells, 2018), these tinkerers are in a community of users that are experimenting, learning and sharing, a "*collaborative community*".

These creators are in a public discourse with YouTube affiliated creators, all reacting to shared knowledge of technology, personal experiences, and online controversy. By identifying these functions and motivations, they undermine perceptions of algorithms as objective and challenge discourses that frame YouTube as being an all-powerful entity. In some cases, the interactions of the collaborative community around a YouTube controversy become so influential that YouTube affiliated creators are obliged to address the controversy (ex. the effects of publishing schedule on content creator mental health). These are cases of YouTube, an enormous subsidiary of tech-giant Google, attempting to engage in a user discourse to protect the perception of the platform and consequently their economic interests. YouTube affiliated content relating to a controversy is an attempt to participate in the collaborative community's online discussion. Rather than supressing speech for capital interests (Feldman, 2017), this participation with the collaborative community's online discussion simply provides more substance for explicit users to reference, share and critique. The results of these controversies demonstrate a network of co-creation and consumption between users and affiliates of the platform, all of the content influences a larger community collaboration around a controversy. The ranging motivations of these separate and sometimes competing parties demonstrates that content creation cannot simply be understood as being typically determined by YouTube economic motivations. Instead, there exists a complex and entangled network of actors producing creative content for various reasons, while being constantly influenced by the network in which they exist. This reality should be recognized by authors that are sceptical of the possibility of agency on platforms that use algorithms.

It cannot be denied that YouTube economic motivations, popular culture, trends and news are influences on the types of content being created and recommended on YouTube. This research supports a broader (and more cluttered) view of user agency as it exists on YouTube. This agency is found in the fluid groups of explicit and implicit users that share knowledge as part of a collaborative community to better comprehend and exist on the platform. The tools to do this are taken from their environment; specifically, the capacity to distribute information on the platform and take advantage of algorithmic functions. A greater knowledge of algorithmic functions allows users to make informed choices motivated by their personal values to either resist or conform to recommendation. This is a user agency informed by algorithms and the contexts in which they are applied and function. Moreover, this user agency as it exists in a collaborative community has shown that it can influence YouTube post-controversies. In doing so, the collaborative community is playing a role in shaping the consequential functions of algorithms in the future.

Conclusion:

YouTube as a platform is chiefly concerned with keeping users on-site for the longest time possible to increase revenue. Due to the massive scale of the platform, to achieve this goal YouTube engineers algorithms that are trained using massive amounts of data collected from users. The findings of this study conform to previously literature, maintaining that a platform's primary goal when collecting data is to better train recommendation algorithms to effectively categorize and manipulate users to remain on the platform. In the case of YouTube recommendation algorithms, data collection is based in the logic that individual self-report of desires or wishes while using the platform is less useful than individuals' actions.

This study found it useful to generalize data collection into two related categories: personal data and behavioural data. Personal data refers to discreet demographic data of a user (age, country, gender, location, previously visited internet sites). Behavioural data refers to the actions of a user when on the YouTube platform (watch-time, viewing habits, navigation habits). Both data types are used to construct categories of user identities, abstractions of individual users into the social categories that are identified as useful to the YouTube platform. Analysis of new incoming data attempts to identify trends that are assumed to be consistent within and between these abstracted categories. The goal of YouTube's mass data collection is to construct abstract categories that may better predict and influence individual action and retain users on the platform. This behaviour conforms to literature arguing that algorithms play an active role in social processes, because the abstracted data created from human categorization causes action in individuals (Beer, 2013).

The results of this study of YouTube data collection, analysis and the construction of online identities based on behaviour conforms to the literature critiquing the techniques and economic motivations of platforms. This research endorses the concerns for human agency raised in the literature review (Brownsword, 2011; Bozdag, 2013; Dormehl, 2014; Schulte, 2016; Finn, 2017; Postigo, 2014; Gillespie, 2018). YouTube data collection targets mass data rather than users' self-reported experience. On multiple occasions throughout the study, it has been noted that user-controlled metrics are given little to no weight when attempting to guide user action on YouTube.

The YouTube data collection techniques revealed in this study certainly could be used to endorse theories of new stages of capitalism. Themes from the theories of a new stage of "platform capitalism" (Srnicek, 2016), where the main source of value in an economy is the refinement of user data, or "surveillance capitalism" (Zuboff, 2015, 2016, 2019), where machine-learning mining of data creates the means of production of surveillance capitalism appear through the study. The final direction of this research is more concerned with experiences of agency among individual users and groups on YouTube. The critical application of a theory of late-stage technology-based capitalism onto the corporate actions and motivations of YouTube would be a fruitful endeavour for future research, as this study has revealed many related findings.

The findings related to the standardization of content, the blocking or obfuscation of content, and mental health/burnout movements demonstrate the material influences and consequences of YouTube recommendation algorithms on content creators and the content that they produce. Using their knowledge of YouTube recommendation, content creators attempt to optimize content for algorithms. In doing so, content creators internalize the economic interests of the YouTube platform. Further, content creators experience sentiments of stress and depression due to their conception of how YouTube recommendation algorithms function. The concept of post-hegemonic power (Lash, 2007) has proven to be a useful theoretical tool for understanding this internalization process and for identifying the resulting loss of agency experienced by users of the YouTube platform. The research shows that the perceptions that YouTube users have of recommendation algorithms are reflected in the content that they create. Content creators internalize the desires of the platform and willingly attempt to conform to these desires without the necessity of YouTube to exercise any kind of traditional authoritarian power. In doing so, the perception and functions of YouTube recommendation algorithms control the types of discourse that may exist on the platform, and the accessibility of users to participate in those discourse.

Although this framework does valuable work in describing the internalization process that content creators experience when producing content for the platform, it failed to account for cases of agency that were identified throughout the research. Like the approach of critical theorists on the topic of human agency in a period of “surveillance capitalism”, the concept of post-hegemonic power fails to entirely account for the complexities of YouTube user experience. These approaches rightly critic the economic structure of contemporary platforms, the problematic consequences of big-data collection, and they do an excellent job of drawing attention to platforms’ desires to influence user activity. However, they fail to represent the experiences of YouTube users in the study that are informed and openly engage with the black boxes of YouTube recommendation algorithms.

By building on Van Dijck’s distinction between explicit and implicit technology users (2009, 2013), a typology of explicit users found during the study is created to better describe the network of diverse users that make up the study; “tinkerers/hobbyists”, “entertainment/commentary (EC) creators” and “YouTube-affiliated creators”. This typology demonstrates the multitude of connections that exist between YouTube users. Individuals and groups use informal self-education methods in a collaborative effort to make black-boxed technology transparent to fellow creators. EC creators consume and transmit versions of learned techniques or critiques to wider audiences of explicit users. These networks of users are constantly interacting with YouTube-affiliated creators, as well as being influenced by platforms and trends coming from outside of YouTube. The result is a messy and interconnected network of diverse explicit users that are influenced by recommendation algorithms. At the same time, users within this network have the technical knowledge to understand and take advantage of algorithms and are co-educating themselves to better understand black-boxed information.

Tinkerers and EC creators use the technics available on YouTube to solve problems and draw attention to controversies. In doing so, the environment of YouTube is allowing these users to enact a type of agency. The gaming of recommendation algorithms has not been considered a common threat for platforms due to the general technical illiteracy of implicit users. Tinkerers and EC creators create community through the sharing of knowledge and personal experience. In this way, these users are enacting agency and taking part in a growing collaborative community that is not only influenced by recommendation algorithms but also consciously responsible for influencing the functions of recommendation algorithms.

On Education:

The findings of this research support previous empirical research supporting that greater knowledge of technology allows individuals greater affordances of agency. Education of the privacy risks and consequences of online action has been shown to affect information sharing habits (Casilli, 2013) (Young, A, Quan-Haase, A, 2009). In those cases, individuals were educated to understand the higher and lower levels of control that they could practice when curating their online profile on social media platforms. Similarly in the cases of online scammers or hackers, individuals with greater levels technological literacy may exercise greater levels of agency online. This is certainly the case for tinkerers and EC content creators on YouTube. These categories of users exercise greater agency on YouTube through their knowledge of the platform and the functions of recommendation algorithms.

The supremacy of technology throughout contemporary society is not only limited to recommendation algorithms on social media platform. The contemporary social world is populated by novel technologies; autonomous vehicles, blockchains and batteries. Portions of social life have begun existing online; communication is hosted by tech-companies and platforms that implement machine learning algorithms. These developments have led to questions of freedom of speech, political polarization, invasions of privacy, dishonest investment activity and adolescent body-image issues. Like YouTube, these platforms and technology companies tend to appear secretive to the public, raising serious concerns for human agency in a contemporary, technological society. However, like so many tinkerers, there are actors taking part in collaborative efforts to make technology transparent, and in doing so are affording agency to individuals.

Davidson (2012) prescribes that early education should include internet literacy, specifically coding. This research makes a similar conclusion, adding that any valuable curriculum for contemporary computational literacy must educate students on the creation and uses of data. A program explaining data collection and the use of machine learning algorithms to process data and identify trends would provide students with a knowledge of the fundamental building blocks of online activity. This education can in turn allow individuals possibilities of agency in their inevitable online lives.

Limitations of study and future directions for research:

Two predominant limitations of this research were a result of the methodology. First, the research was limited by only using qualitative data. As has been demonstrated in the literature review, all behaviour online becomes data points that can be gathered and analysed. Considering that the content of the research is concerned with data-based recommendation algorithms, quantitative methods of data analysis may have been useful to test the validity of some informant claims. Second, direct long-form interviews with creators, specifically those informants most often referenced in the study, would have been a valuable addition to the collected data. Long-form interviews would have allowed informants to reflexively comment on content that they had published online concerning recommendation and YouTube and would have allowed a richer understanding of their personal experiences with "The Algorithm". Due to the public facing nature of internet content creators, one-on-one long form interviews may have shown a less curated side of their personality and allowed a more genuine appraisal of their feelings about agency online.

Finally, an especially useful tool of analysis that emerged from this research was the typology of explicit users. There was variation amongst users that were categorized as belonging to each type. The category of tinkerer was particularly interesting because so many content creators assigned to this category appeared to have different motivations for creating educative content on YouTube. A possible future direction of research could build upon the typology of tinkerer users and apply this to different social media platforms.

This study has demonstrated the influence of YouTube recommendation on individual users. These influences and the economic motivations behind them will continue to play a role in discussions about social media platforms' place in different societies. What do private platforms owe their users? When should private platforms be held responsible for manipulation? Can users have greater control over their online data? A greater knowledge and perception of the functions of algorithms will help inform those discussions and encourage individual agency in online spaces.

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