Oñati Socio-Legal Series (ISSN: 2079-5971)
Oñati International Institute for the Sociology of Law
Avenida Universidad, 8 – Apdo. 28
20560 Oñati – Gipuzkoa – Spain
Tel. (+34) 943 783064 / opo@iisj.net / https://opo.iisj.net

Beyond possessive agency: TikTok, YouTube, and the inadequacies of GDPR, OSA, DSA, and AIA

OÑATI SOCIO-LEGAL SERIES FORTHCOMING
DOI LINK: HTTPS://DOI.ORG/10.35295/OSLS.IISL.2237
RECEIVED 6 JANUARY 2025, ACCEPTED 27 FEBRUARY 2025, FIRST-ONLINE PUBLISHED 27 MARCH 2025

WILL MBIOH*

Abstract

This paper critiques the foundational assumption underpinning UK and EU regulations—including the GDPR, Online Safety Act, Digital Services Act, and Artificial Intelligence Act—that agency is a possessive attribute rooted in individual autonomy. Using YouTube and TikTok as case studies, it examines how advanced recommendation systems powered by deep neural networks, multi-armed bandits, and reinforcement learning blur the boundaries between user agency and platform influence. Drawing on feminist relational theory and Karen Barad's concepts of intra-action and diffraction, the paper argues that contemporary platforms generate a distinct, relational form of agency that operates interstitially in the 'in-between' of user actions and algorithmic systems. This emergent directive power challenges existing law in the EU and UK concerning online safety, which position platforms as neutral tools rather than co-constitutive entities. The paper calls for a re-imagination of legal ontologies and for a shift from possessive agency to relational governance to address the complexities and risks posed by modern algorithmic assemblages.

Key words

GDPR, OSA, DSA, AIA; algorithmic governance; deep neural networks; feminist new materialism; intra-action and diffraction

Resumen

Este artículo critica el supuesto fundamental en el que se basan las normativas del Reino Unido y la UE –incluidos el RGPD, la Online Safety Act (Ley de Seguridad en Línea), la Ley de Servicios Digitales y la Ley de Inteligencia Artificial– de que la agencia es un atributo posesivo arraigado en la autonomía individual. Utilizando YouTube y TikTok como casos de estudio, se examina cómo los sistemas avanzados de recomendación impulsados por redes neuronales profundas, bandidos multibrazos y aprendizaje de refuerzo desdibujan los límites entre la agencia del usuario y la influencia

* Dr. Will Mbioh, Senior Lecturer in Law, Kent Law School, University of Kent, Canterbury, United Kingdom. The Registry, Canterbury, Kent, CT2 7NZ. Email: W.R.Mbioh@kent.ac.uk

de la plataforma. Partiendo de la teoría relacional feminista y de los conceptos de intraacción y difracción de Karen Barad, el artículo sostiene que las plataformas contemporáneas generan una forma distinta y relacional de agencia que opera intersticialmente en el “entremedio” de las acciones de los usuarios y los sistemas algorítmicos. Este poder directivo emergente desafía la legislación vigente en la UE y el Reino Unido en materia de seguridad en línea, que sitúa a las plataformas como herramientas neutrales en lugar de entidades co-constitutivas. El artículo aboga por una reimaginación de las ontologías jurídicas y por un cambio de la agencia posesiva a la gobernanza relacional para abordar las complejidades y los riesgos que plantean los ensamblajes algorítmicos modernos.

Palabras clave

RGPD, OSA, LSA, LIA; gobernanza de algoritmos; redes neuronales profundas; nuevo materialismo feminista; intra-acción y difracción

Table of contents

1. Introduction

In the UK and EU, the primary laws governing user safety on social media and video-streaming platforms are as follows: the General Data Protection Regulation (GDPR) (2016), which regulates the collection and processing of personal data; the Online Safety Act (OSA) (2023) in the UK and the Digital Services Act (DSA) (2022) in the EU, both of which focus on the duties and responsibilities of platforms regarding the content they amplify and curate (see OSA, §§ 7–12; DSA, arts. 16, 23–24); and the Artificial Intelligence Act (AIA) (2024) in the EU, which prohibits specific uses of algorithmic systems, particularly manipulative or deceptive practices such as subliminal messaging and the targeting of vulnerable groups like children (see AIA, art. 5).

Despite their differences, these regulations share a foundational and implicit assumption about agency, one rooted in the traditional liberal conception of possessive agency, grounded in the notion of the autonomous legal subject, wherein agency is understood as internal to the individual (see GDPR, arts. 5–9, 12–14; DSA, recitals 50, 54, and arts. 14–15; OSA, §§ 14–15). In the context of platforms, this conception manifests as the belief—or, more specifically, an objective in law—that users act upon the platform, with their will and intentions reflected in their interactions and engagements (e.g., OSA, §§ 26–27, 38; GDPR, recital 32, art. 14). Platforms, in this model, are viewed as distinct and separate from users—tools that individuals use to mirror and reflect their intentions.

This understanding is not limited to law but extends into academic scholarship, particularly in discussions around echo chambers and the surveillance platform economy (Sunstein 2018, Zuboff 2019). In these contexts, the dominant concern is that agency, being fundamentally individualistic and possessive, enables users to exercise their agency by engaging with passive platforms that reinforce, echo, and mirror their intentions and biases (Sunstein 2017, 2018). Platforms are commonly imagined as external tools or mirrors, reflecting user intentions and biases, rather than as entities that fundamentally shape or constitute that intention or agency (Sunstein 2018, Brown *et al.* 2022). Similarly, in the field of surveillance capitalism, a parallel concern emerges: Skinnerian behavioural conditioning. Here, the primary worry is that platforms, particularly through their recommendation systems, are designed to exploit users' internal desires and physiological needs for dopamine hits via variable rewards (Alter 2017, Zuboff 2019). This model assumes that users possess an internal drive for such rewards and that platforms act as external systems, mirroring and reinforcing this desire by providing random variations that trigger dopamine responses (Zuboff 2019).

Across these contexts—whether in law, echo chamber theories, or behavioural conditioning models—the individual and their behaviours, intentions, and biases are treated as the dominant unit of analysis. Agency is consistently conceptualised as an internal and distinct attribute of the individual, operating within a framework that assumes a dualistic separation between the individual and the platform (Barad 2007). While the relationship between users and platforms is acknowledged, it is primarily understood as one of interaction between two distinct entities. The individual's agency is seen as separate from the platform: either the platform reflects and echoes back the user's intentions (as in echo chamber theories or legal frameworks) or it acts upon the user's internal drives and desires (as in behavioural conditioning models). Even when the platform seeks to influence user behaviour, it is imagined as responding to the user's internal possessive agency rather than co-constituting or reshaping it (Sunstein 2017, 2018).

Using YouTube and TikTok as case studies, and the foundational algorithmic systems that drive them (mainly, deep neural networks, the law of large numbers, multi-armed bandits, and reinforcement learning), I will begin by introducing these foundational techniques and argue that the current framing of agency neglects the ways in which modern platforms, particularly those powered by advanced recommendation systems, fundamentally challenge these assumptions by blurring the boundaries between individual agency and platform influence. In that, the directive and constitutive power of these systems is now so immense that the gap between what these systems predict and what users do is so negligible as to not be so much erased but effectively reconfigured and rendered indistinguishable in practice.

After that, and drawing from feminist relational theory and new materialism (Alaimo and Hekman 2008, Downie and Llewellyn 2011, Nedelsky 2011, Harris 2021)—particularly Karen Barad's concepts of intra-action and diffraction (Barad 2007, 2014)—I will argue that what has emerged is not an individual, possessive form of agency but rather a distinct mode of action and being. This mode operates interstitially, existing in the 'in-between' spaces of becoming and emergence, where user intentionality and the platform's directive and constitutive power converge. It is less about agency as something owned or possessed by the individual and more about a gravitational pull or dynamic force that arises relationally, shaped by the entanglement of user actions and algorithmic systems (Barad 2007, Nedelsky 2011).

As such, I will finish by contending that this mode of agency generates significant challenges to the current applicable law that need more focused attention by legal scholars. These challenges are particularly acute for users in vulnerable contexts and high-stakes scenarios, where the entangled dynamics of agency and algorithmic power can exacerbate marginalisation and lead to harmful trajectories. Such risks demand a rethinking of regulatory assumptions to account for the relational and constitutive nature of these systems, especially given their potential to shape users' decisions and outcomes in significant and often detrimental ways.

2. The backbone of algorithmic recommendations: An overview of deep neural networks

The recommendation systems on platforms like YouTube and TikTok are incredibly complex and sophisticated (Covington *et al.* 2016, Fang *et al.* 2020, Smith 2021). The computational power and infrastructure required to run them are immense—not only to store the vast amounts of data, information, and software necessary but also to execute the advanced mathematical modelling and machine learning techniques that underpin these systems (Covington *et al.* 2016, Gao *et al.* 2017, Salehi Rizi and Granitzer 2017). What feels intuitive and organic to users (the feeling, as the *New York Times* put it, that they are "reading your mind"(Smith 2021)) is, thus, the result of extraordinarily complex processes that we cannot fully capture in any detail here. Nevertheless, for our purposes, a high-level understanding of some of the key techniques foundational to these systems should suffice.

The operation of recommendation systems on platforms like YouTube and TikTok can be broadly understood through two interconnected stages (Covington *et al.* 2016, Smith 2021). The first stage occurs offline, independent of users' real-time engagement (Chen *et al.* 2024). This involves training the predictive model that will later be used when users engage with the platform. During this phase, companies collect and aggregate vast quantities of historical data—billions of user interactions, behaviours, and activities on their platforms—and process this dataset using machine learning (a method of teaching computers to identify patterns, make decisions, or predict outcomes based on data, without being explicitly programmed for every scenario, while improving over time as they process more information) (Covington *et al.* 2016, Smith 2021).

To give a sense of the sheer scale and variety of this data, platforms gather both explicit and implicit data (referred to as 'signals') from users (Covington *et al.* 2016, Smith 2021). Explicit signals include actions such as liking or disliking a video, subscribing to a channel, commenting on content, saving videos to playlists, and sharing them with others. These are the visible, intentional actions users take. In addition, platforms collect implicit signals, which are often less obvious but equally significant in shaping recommendations. These include data such as whether a user watched a video to completion, paused it, replayed certain sections, or skipped ahead (Covington *et al.* 2016, Hu *et al.* 2018). It also includes the time a user hovers over a thumbnail, the speed and direction of their scrolling, the frequency with which they revisit certain types of content, and even the time of day they are active. Moreover, beyond these behavioural signals, platforms gather contextual information such as the user's device type, operating system, location, language preferences, and internet speed. They may also incorporate demographic data, inferred or provided directly by the user, including age, gender, and regional identifiers (Covington *et al.* 2016). Taken together, this data is colossal in scale. With billions of users worldwide generating millions of interactions every second, platforms process petabytes of information daily (for context, a single petabyte is equivalent to over 500 billion pages of standard printed text or approximately 13 years of continuous high-definition video) (Covington *et al.* 2016, Georgevici and Terblanche 2019).

The machine learning technique that processes this data is called a Deep Neural Network (Covington *et al.* 2016, Vieira *et al.* 2020). While it is often described as an algorithm that mimics the structure of the human brain—drawing analogies to neurological and synaptic architecture (Montesinos López *et al.* 2022)—a more intuitive way to imagine it might be as a vast and immensely complex, finely tuned, highly calibrated machine, apparatus, or assemblage of hundreds, thousands, or even of thousands (in the case of 'deep' networks) of interconnected layers of algorithms functioning together to complete a task (Montesinos López *et al.* 2022).

Powered by supercomputers (so-called because they are vastly more powerful than regular computers, capable of performing trillions of calculations per second and handling immense datasets simultaneously through advanced parallel processing), these networks are capable of detecting incredibly subtle and granular relationships and patterns within the massive datasets they are fed (Covington *et al.* 2016). These datasets are analysed based on billions of parameters—factors or elements—that enable the network to uncover patterns and relationships across hundreds of billions of data points or signals and an almost incomprehensible number of dimensions, all with the singular aim of optimising their predictive capacity to increase watch time—whether by mere fractions of a second, milliseconds, or minutes—knowing that even the smallest incremental gains at this immense scale result in significant overall impact (Covington *et al.* 2016).

Once the predictive model has been trained, in the second phase of this process, it is used to generate formulas or recommendation logics that the model can use in real-time on live users (Covington *et al.* 2016, Chen *et al.* 2024). These formulas perform two essential functions. First, they enable the system to select potential candidates from a vast corpus of content—billions of videos or other forms of media. Second, they rank these selected candidates to identify the content most likely to maximise user engagement and retention.

However, it is important to understand that the formulas and parameters used to determine them are not fixed. They change and are fine-tuned over time, influenced by new historical data and ongoing optimisation efforts to improve predictive accuracy (Covington *et al.* 2016, Smith 2021, Chen *et al.* 2024). Because these systems rely on deep neural networks, their operation should not be thought of as following simple, static rules, such as "if a user watches video A, recommend video B." Instead, they function more like methods of reasoning based on a vast array of learned factors to make finely balanced and contextual decisions about content selection and ranking (Covington *et al.* 2016, Chen *et al.* 2024).

That is, it is less like following a step-by-step recipe to cook a dish and more akin to the experience of mastering a skill through repeated practice, such as learning how to parachute. After undergoing countless hours of training and practice, a parachutist develops a particular orientation and set of reflexes. They acquire an almost instinctual understanding of how to position themselves in the air, when to deploy the parachute, and how to adjust for external factors to ensure a safe landing. This understanding becomes embodied—a form of muscle memory or a deeply ingrained sense of what to do in specific contexts, refined over time and shaped by countless repetitions. Similarly, these algorithms develop a kind of 'reflexive intelligence' through processing hundreds of billions of data points about user behaviour and acquire the capacity to discern what to do in a given context—not by following a rigid set of instructions but by drawing on patterns and relationships learned through vast amounts of training (Covington *et al.* 2016, Chen *et al.* 2024). Over time, they build a highly sophisticated sense of what actions (in this case, recommendations) are likely to achieve the desired outcome, such as maximising user engagement.

3. The TikTok algorithm: A simplified view of ranking and weights

Although these formulas or logics are typically considered highly commercially sensitive and are treated as trade secrets, due to the New York Times investigation into TikTok (Smith 2021), we have a much-simplified version of one such formula that gives us an idea of the factors likely considered when recommending content and training the machine offline.

What we know is that TikTok's recommendation engine uses this formula to score or rank videos for recommendation based on their potential to engage a user: Score = (P_{like}

$\times V_{like}) + (P_{comment} \times V_{comment}) + (E_{playtime} \times V_{playtime}) + (P_{play} \times V_{play})$. This formula combines predictions about user behaviour with weights assigned to specific actions to determine which videos are most likely to keep the user engaged. Each term in the formula represents a combination of two components: a prediction and a weight. The prediction, calculated by TikTok's machine learning models, estimates the likelihood of a user taking a particular action (e.g., liking a video). The weight, on the other hand, quantifies how much importance or value the system places on that particular action in influencing the overall recommendation score (Vieira *et al.* 2020). It acts as a multiplier that adjusts the significance of the corresponding prediction within the formula. For example, if the system determines that 'liking' a video is a strong indicator of engagement, the weight for 'likes' (Vlike) will be higher, meaning that the Plike (probability of liking) will have a larger impact on the final score. Weights are fine-tuned during the training process to optimise the system's ability to maximise user engagement (Covington *et al.* 2016, Vieira *et al.* 2020).

For example, P_{like} is the probability that a user will like a video, based on their past interactions and inferred preferences, while V_{like} indicates how much value a like contributes to the video's overall score. Similarly, $P_{comment}$ predicts the likelihood of a user leaving a comment, and $V_{comment}$ determines how influential that behaviour is in the recommendation process. $E_{playtime}$ measures how long the video is watched—an important signal of engagement—while $V_{playtime}$ reflects its weighting in the score. Finally, P_{play} estimates the probability of a user choosing to watch the video at all, with V_{play} accounting for the significance of simply pressing 'play.'

The final product of this calculation is 'the score,' which is a *relative* measure that the algorithm uses to rank videos. A higher score means the video is more likely to capture user attention and keep them engaged, so it's more likely to be shown to them. The algorithm calculates similar scores for other videos, and the ones with the highest scores make it into the user feed. As such, this score does not have an absolute meaning outside of the algorithm (Covington *et al.* 2016, Vieira *et al.* 2020, Smith 2021). Instead, it is part of a ranking system where each video competes with others. The process is dynamic and contextual—another user might see a completely different ranking because their probabilities and weights would differ based on their inferred preferences and behaviour.

4. Why more data means better predictions: The role of the law of large numbers

The significant advantage that platforms like YouTube and TikTok possess in determining and fine-tuning weights—the relative importance assigned to specific factors (e.g., likes, comments, playtime)—in their formulas is their access to an extraordinarily large volume, variety, and diverse sources of user data and behaviour (Covington *et al.* 2016, Smith 2021, Chen *et al.* 2024). This vast scale of data enables these platforms to exploit the statistical principle of the law of large numbers, alongside the scaling laws of large models, to achieve extraordinary predictive accuracy and effectiveness in their recommendation engines (Révész 2014, Conti *et al.* 2018, Zhang *et al.* 2024). The statistical principle of the law of large numbers of states that as the size of a dataset increases, the average result of random variables (in this case, user behaviours) becomes more predictable and converges to the expected value. In the context of platforms like YouTube and TikTok, this principle allows their algorithms to smooth out the inherent randomness in individual user actions by aggregating behaviour across millions or even billions of users (Covington *et al.* 2016). This aggregation reduces the influence of outliers and 'noise' and enable the system to identify general trends and behavioural patterns with remarkable precision (Révész 2014, Conti *et al.* 2018). However, the law of large numbers relies on having access to an immense volume of data; it cannot operate effectively at the level of individual users, where behavioural data is too sparse and noisy to extract meaningful patterns. At an individual level, randomness dominates and predictions based on a single user's actions (that is, the idea of personalisation as typically understood) highly unreliable; i.e., the typical notion of personalisation—where a platform tailors content uniquely for an individual based solely on their explicit preferences and actions—fails because isolated data points lack the statistical stability needed to support accurate predictions.

In parallel, the scaling laws of large models describe how the performance of machine learning models improves predictably as the size of the model (measured in parameters) and the dataset (measured in training examples) increase (Zhang *et al.* 2024). Larger models have the capacity to learn and represent complex relationships within data, including subtle and multi-dimensional patterns that smaller models may miss (Covington *et al.* 2016, Zhang *et al.* 2024). For example, a recent detailed study of recommendation systems (Zhang *et al.* 2024) shows that larger models are also more data-efficient, meaning they can extract more value from a given dataset compared to smaller counterparts. When applied at the scale of platforms like YouTube and TikTok, these scaling laws allow their recommendation systems to fine-tune predictions and make highly accurate inferences about user behaviour.

Importantly, such predictive accuracy is possible even in the presence of gaps in the data due to advanced techniques that fill these voids with synthetic or inferred information (Chen *et al.* 2024). When platforms like YouTube face missing or sparse data—whether it's a user who hasn't interacted much, a newly uploaded video with no views, or gaps in user preferences—they can employ different strategies to 'plug the gaps' and maintain their predictive power. For instance, synthetic data generation creates realistic but artificial data points that mimic the patterns and trends observed in existing datasets. Imagine a new video with no initial viewers: the system might use similar videos' past data to simulate expected behaviours and help the model understand how audiences might react. Similarly, for new or infrequent users, knowledge graphs link sparse user data to related attributes (like favourite genres or viewing history) to infer likely preferences. In cases where only limited individual-level data exists, transfer learning allows the system to draw insights from related groups or contexts and to share knowledge between them to make accurate predictions (Covington *et al.* 2016, Chen *et al.* 2024).

When the statistical principle of the law of large numbers, the scaling laws of large models, and advanced techniques like synthetic data generation, knowledge graphs, and transfer learning are combined, recommendation systems can achieve extraordinary levels of predictive accuracy. By leveraging the immense volume and diversity of user data, the law of large numbers means that randomness in individual behaviour is smoothed out, allowing the system to detect stable patterns across billions of users. Simultaneously, scaling laws enable large machine learning models to capture complex, multidimensional relationships within the data, refining predictions with exceptional granularity and subtlety. Advanced techniques address gaps or sparse data, ensuring consistent predictive power even in less-than-ideal conditions. This synergy makes it possible for systems to approach prediction accuracies exceeding 90% for key engagement metrics like watch time, as deviations between expected and actual behaviours become statistically negligible at scale (Révész 2014, Covington *et al.* 2016, Zhang *et al.* 2024). That is, at these levels of predictive accuracy, the gap between what the system predicts users will do and what users actually do becomes, over time, vanishingly small so that instances where the system's predictions deviate from user behaviour are not just infrequent but occur within an increasingly narrow band of exceptions or errors.

5. Finding the best path: How multi-armed bandits use reinforcement learning to explore and exploit

In addition, when the predictive models go live, platforms like TikTok and YouTube typically employ what are known as multi-armed bandits as a form of reinforcement learning—a machine learning technique where an algorithm learns in real time by receiving 'rewards' or 'punishments' based on how well it performs a specific task (Covington *et al.* 2016, Silva *et al.* 2022). More precisely, the term 'multi-armed bandit' originates from probability theory and statistics based on an analogy to a gambler at a row of slot machines (referred to as 'one-armed bandits'). Each slot machine represents a different option with an unknown probability of providing a reward. The gambler's task is to figure out which slot machine is most rewarding by balancing two competing actions: exploiting the machine that seems to give the best payouts based on previous pulls and exploring other machines that might yield even higher rewards (Feng 2024).

In the context of a recommendation system, the algorithm plays the role of the gambler, and the 'slot machines' represent different types of content it could recommend to users. The rewards, in this case, are user engagement metrics, such as watch time, likes, shares, or clicks. A 'reward' occurs when a user engages with the content in a way that aligns with the system's goal—most often, extending time spent on the platform. Conversely, a 'punishment' happens when the user disengages, such as skipping the video, closing the app, or abandoning a suggested pathway.

The algorithm continuously experiments with these 'machines,' or content types or sequences or timing of content, to refine its strategy. Through exploitation, the system recommends content similar to what the user has already engaged with, betting on known tendencies. However, exploration is equally important: the algorithm tests alternative content types or recommendations, seeking to uncover new interests or engagement opportunities that might lead to even higher rewards. This exploratory process involves observing how users react to unfamiliar or unexpected content and recalibrating the system's predictions and strategies based on these reactions. However, in practice, the distinction between exploitation and exploration becomes fluid, as both actions contribute to the same overarching goal: maximising user engagement. By exploiting known patterns, the algorithm builds on its existing understanding of user preferences, while exploration allows it to refine and expand this understanding, ensuring its strategies remain dynamic and adaptable (Kwa *et al.* 2022).

Significantly, the multi-armed bandit does not only rely on feedback from an individual user. It also incorporates data from other users with similar behaviours or signals, using the rewards and punishments it receives across the platform to continuously refine its decision-making. These experiments in exploration and exploitation are conducted routinely and at scale so that the algorithm improves over time due to scaling laws and the law of large numbers. That is, the more experiments and tests it runs, the better the algorithm becomes at determining when to stick with an exploitation strategy and when to switch to exploration. It also learns to adapt to the specific factors and contexts that influence these decisions to further refine its approach to optimise engagement (Feng 2024).

This real-time learning means that all users on the platform are effectively training the system as they engage with it. The distinction between simply using the platform and contributing to the training of the multi-armed bandit blurs. This happens because what the platforms effectively do is turn every single action—or inaction—that users take on the platform into a form of input for a distributed training network for the multi-armed bandit. Every engagement, no matter how minor, feeds into the algorithm. Through this process, users are not only training the algorithm to become increasingly effective at keeping them on the platform for as long as possible, but they are also collectively training the system to refine its ability to sequence and strategise content for others with similar engagement patterns or behavioural profiles (Zou *et al.* 2019, Sharma *et al.* 2021, Stamenkovic *et al.* 2022, Feng 2024).

In effect, users are training the system to trap and retain themselves while simultaneously contributing to the system's ability to do the same to others. This creates a feedback loop where the algorithm becomes ever more adept at extending watch time across vast groups of users, leveraging both individual and collective behavioural signals (Zou *et al.* 2019, Sharma *et al.* 2021, Stamenkovic *et al.* 2022, Feng 2024). As this happens, the bandits become exceptionally capable of extending watch time. They also grow increasingly precise at reducing the gap between their predictions of what content will extend user watch time or engagement and the user's actual behaviour.

6. Beyond skinner and bias: The emergent forces of modern recommendation systems

What this means, in effect, is that what platforms like YouTube and TikTok are doing to retain user engagement is fundamentally different from the explanations typically offered within the models of surveillance capitalism or persuasive technology literature. These dominant models generally explain the addictive nature of platforms or the tendency of users to remain hooked through two main ideas.

The first explanation, rooted in Skinnerian behaviourism, holds that users continue engaging with platforms because they are designed to condition behaviour much like slot machines (Alter 2017, Zuboff 2019). The idea is that platforms provide variable rewards—unpredictable outcomes that trigger a dopamine rush—encouraging users to repeatedly roll the proverbial content wheel in anticipation of the next 'treat.' In this model, it is the uncertainty, randomness, and variability of rewards that create a sense of compulsion that keeps users engaged as they chase the next treat of content.

The second explanation comes from persuasive technology design and choice architecture theories, particularly those influenced by behavioural economics and psychology. This perspective argues that users stay on platforms due to inherent cognitive biases (Fogg 2009, Sunstein 2018). For example, echo chamber theories suggest that users are driven by confirmation bias, seeking content that reinforces their pre-existing beliefs. Similarly, group-based biases, such as homophily (the tendency to gravitate toward like-minded groups), are thought to explain why users cluster around specific content and communities (Sunstein 2017, 2018, Brown *et al.* 2022).

Both models (i.e., behavioural conditioning and echo chambers) suggest that the compulsion to remain on the platform arises from internal psychological mechanisms or biases, portraying extended watch time as the result of something intrinsic to the user's mind. However, while these explanations hold some validity, my contention is that they are not fully consistent with what we now understand about how platforms like YouTube and TikTok operate. Based on what is known about their recommendation systems and the techniques they deploy, these platforms do not primarily rely on such mechanisms to drive engagement. Instead, their approach is different in significant ways.

At a fundamental conceptual level, platforms like TikTok and YouTube do not rely on or design their systems based on individual behaviours, actions, or internal states in isolation. This is due to reasons already discussed, including the reliance on large datasets, the importance of those datasets reaching a scale where the law of large numbers begins to apply, and the ability to extract meaningful patterns from aggregate data. What matters here is not what an individual thinks, desires, or believes; rather, these individual characteristics are often treated as noise, randomness, or variability within the larger system (Conti *et al.* 2018, Xin *et al.* 2023). The focus is on the relational dimension of the individual—what their signals mean in relation to vast amounts of aggregated data, patterns, trends, and inferred behaviours. In this sense, while the individual is central as a unit of analysis, they are also peripheral to the system's broader goals of increasing predictive accuracy and achieving convergence between predicted and actual behaviours (Covington *et al.* 2016).

Personalisation, therefore, is not so much about the system reflecting the intentions or behaviours of the user, nor necessarily about training or conditioning the user to chase some kind of reward. The key idea is the generation of a form of force, power, or gravitational pull, arising from the sheer sophistication of the system and its computational capacity. This creates a situation where the user experiences a feeling—a sense of being drawn in—so that their behaviour is consistent or made consistent with the system's predictions. It's not necessarily about the algorithm reflecting the user's intention; rather, it's about creating circumstances and conditions where it's not that the user's intentions don't matter, but more that they feel engaged, as though the content being presented is exactly what they would have chosen next *if* they were asked to select it (Covington *et al.* 2016).

This is different from simple prediction because it operates in that space, that line, that moment of intersection between prediction and actual behaviour. It's about the specific gap, the precise moment, and the relational effect that emerges in that space. This effect is distinct because it is not solely about the user's intention, nor is it entirely about the system's design or operation. Instead, I contend, it arises from the entire assemblage of components working together: the historical data used to train the algorithm, the various algorithms, functions, weights, formulas, and parameters processed by the deep neural network, the immense computational power driving it all, the reinforcement learning enabled through multi-armed bandits, and the principles of the law of large numbers (Covington *et al.* 2016, Vieira *et al.* 2020, Feng 2024).

These elements converge in that moment, creating a condition, a force, a feeling, a pull—a relational effect that exists and operates only by virtue of all these components acting together (Smith 2021). It is an immense form of power that cannot be easily reduced to concepts like autonomy or coercion. It exists as a phenomenon of the assemblage itself, something far more complex and relational in nature.

7. Relational autonomy and intra-action: Distributed agency in algorithmic assemblages

What I mean by this is: it is now trite and well-established in the fields of feminist relational theory, feminist materialism, new materialism, and post-humanism that the idea of agency—or, for that matter, the very idea of ontology (what exists in the world and how things relate to themselves)—is inherently relational (Barclay 2000, Benson 2014, Bergsdóttir 2017, Harris 2021). It is not something that can easily be understood as a possession of any individual entity, whether human or non-human (Van Wyk 2012, Elwood and Leszczynski 2018, Draude 2020).

That is to say, it is now generally accepted within these fields that the liberal idea of the autonomous subject, conceived as a self-contained entity with the capacity to act upon the world, is limited. This understanding of agency as a property or characteristic of the individual, bounded and self-contained, assumes a clear distinction between the self and the world as separate and distinct (Mackenzie and Stoljar 2000, Stoljar 2013, Mackenzie 2019). While this perspective might capture certain aspects of agency—such as those linked to internal states or subjectivity that operate within the human individual—it remains incomplete. It centres too heavily on the human as the primary site or source of agency, prioritising the individual as the locus of power, capacity, and significance in shaping and acting upon the world (Barad 2007).

What scholarship in these fields makes clear is that to be human, and to exist ontologically, is to be in relation to and in relationships with others (Morton 2013, Harris 2021, Mauthner 2021). These relationships are not limited to other human beings but extend to the material world, social institutions, practices, discourses, values, artefacts, objects, and effects (Barad 2003, Bennett 2004, Feniak 2021). Karen Barad, like many others in this field, argues that agency is not an individual possession. It is not something we have, nor can it be imagined as a thing that resides within the isolated human subject (Barad 2007, Harris 2021). Instead, agency is distributed and constituted through relational dynamics and processes of intra-action (Rouse 2016, Hollin *et al.* 2017).

Intra-action, as Barad conceptualises it, refers to the way agency emerges in the interstitial spaces, moments, and processes—what exists in the 'in-between' as effects of relational encounters (Barad 2007, Harris 2021). Agency, understood in this way, is not owned; it is not a fixed property. It is a phenomenon that emerges from relational dynamics, shaped and given form by these intra-actions. It is through these dynamics—and their processual effects—that agency takes on its agential capacity, its ability to act upon the world, have an effect, and be affected by the world.

Accordingly, this is why I draw from Barad and feminist relational theory to conceptualise the distributed agency we observe in the relational encounters between algorithmic platforms and users. This agency is fundamentally intra-active and *interstitial*. It is not something that users possess, nor is it solely the product of the technical, algorithmic, and computational assemblages of platforms. Rather, it exists in the relational space that emerges between users and platforms. As feminist relational theory has shown, this space is not one of absolutes, fixed categories, or binaries, but one of becoming—a relational effect that unfolds through entanglements and intra-actions (Dillen 2018, Elbanna 2018).

What I mean by this is that the sense, the feeling, the effect, or the manifestation that arises when the algorithmic assemblage of platforms operates to recommend, direct, or steer the user toward a particular behaviour is not something that can be fully attributed to the user's intention or any internal state within them. Nor is it something entirely external to them, dictated solely by the platform's algorithmic processes. Instead, it emerges as a relational phenomenon—an interstitial force that exists in the space and moment where these elements intersect.

And so, the user does not so much act as they intra-act. It is not so much that they intend, but rather that the feeling or behaviour to act is co-constituted (Bozalek and Zembylas 2017, Harris 2021). In this way, the user does not fully decide; instead, the feeling and experience unfold—not as something they control or consciously intend, but as something that is felt, done, performed, and brought into being. It is a process, not of isolated agency, but of relational emergence, where the act itself arises through and within the entanglement of user and system.

As such, this unfolding can be understood as what Karen Barad terms diffraction (Barad 2014), because it suggests the dynamic and relational nature of agency and causation within an assemblage. Barad's concept of diffraction, borrowed from quantum physics and feminist relational theory, seeks to capture how phenomena unfold not in linear or predictable ways, but as patterns of interference and relational becoming (Barad 2014). Diffraction captures how elements—be they material, social, or discursive—intra-act, entangle, and mutually shape one another to produce emergent effects that cannot be attributed solely to any individual component (Bergsdóttir 2017, Harris 2021).

When applied to the phenomenon of recommending, the process is not fixed or determined in advance; instead, it is emergent, shaped by the intersection of countless variables—historical data, algorithmic weights, user preferences, optimisation logic, and the platform's overarching goals. The patterns of intra-action that result are not reflections (a static mirroring of inputs) but diffractions—complex, nonlinear patterns of interference and emergence. These patterns create something new: a distributed agency that exists neither solely within the user nor entirely within the algorithm, but as a relational phenomenon that only arises through their entanglement.

8. Law and possessive agency: DSA, OSA, GDPR, AIA

Yet, when we examine the major laws aimed at protecting users from harm in the EU and UK—such as the General Data Protection Regulation (GDPR) (2016), the Digital Services Act (DSA) (2022), the Online Safety Act (OSA) (2023), and the Artificial Intelligence Act (AIA) (2024)—a foundational assumption underpins them: the idea that agency is a possessive characteristic. That is, agency is treated as an inherent property of the individual, something users possess internally and can exercise autonomously to shape their actions, safeguard themselves, and manage their online experiences.

Take the GDPR as an example. Foundationally, the GDPR is built on the assumption that individuals possess agency as an internal quality that enables them to consent to the processing of their personal data or to enter into service contracts that require such processing (GDPR, arts. 4(11), 5, 7, 13–14). This internal, self-contained agency legitimises the processing of data under the GDPR. Once users engage with platforms, it is further assumed that their agency allows them to protect themselves by exercising their rights. For instance, they may withdraw consent, object to the processing of their data, request data erasure, or seek rectification (GDPR, arts. 15–18). The fundamental idea here is that users possess an autonomous, self-contained agency that empowers them to undertake these actions independently.

Following this reasoning, when users encounter recommendations on platforms and act on them—whether by engaging with or ignoring the suggested content—the assumption is that their actions reflect their internal agency. This framework conceptualises agency as entirely within the user, as a property that governs their intentions and decisions, and regards the platform merely as a neutral tool. Much like a hammer, the platform is thought to be an instrument that users manipulate to express their own will or intentions.

However, this understanding has significant limitations. Because data protection laws, and the broader legal architecture governing platforms, are built on this possessive, liberal conception of agency, they lack the language or conceptual space to recognise how platforms might position users in ways that influence, co-constitute, or even constrain their agency. Modern recommendation systems, particularly those powered by advanced algorithmic processes, as I have argued, possess directive power far beyond the simplistic 'tool-like' role these laws envisage. The laws fail to address the possibility that user agency could emerge relationally or be fundamentally shaped by the platform's operations.

It might, however, seem reasonable to question how my argument holds when laws such as the UK's OSA and the EU's DSA impose obligations on platforms to identify and remove illegal content (OSA, §§ 9–12; DSA, arts. 7, 16, 23, 34–35). Would this not suggest that the concept of agency as an individual, possessive characteristic is not as foundational as I propose? These laws, however, do not appear to fundamentally challenge the core assumption that agency is primarily understood as an individual, internal possession. The presence of legal restrictions on criminal behaviour—whether in the context of platforms or elsewhere—does not negate the broader conception of agency as a foundational principle. Just as laws prohibiting acts like theft or homicide do not invalidate the idea of personal autonomy and responsibility, so too do these laws fail to undermine the assumption that users retain individual agency when engaging with platforms.The focus of these laws on illegal speech and conduct does not alter the foundational idea that users are perceived as possessing the internal agency to decide what they wish to watch or engage with online (DSA, arts. 7, 16, 23, 34, 35, 45; OSA, §§ 9–10, 26–27, 71, 121). These laws are primarily carving out specific categories of prohibited content but do not alter the broader foundational model. In fact, the safeguarding provisions in these laws reinforce this assumption. For example, under the OSA, one of the ways users are protected from harm is by requiring platforms to provide them with the option to exercise their individual agency, such as by setting filters for words or types of content they do not wish to encounter (OSA, §§ 15, 22, 70, 77). Similarly, the DSA obliges platforms to provide users with the option to opt out of personalised recommendations (DSA, art. 38).

Even in cases where platforms are required to avoid certain practices, the underlying possessive foundations of agency remain intact. For instance, the DSA includes provisions prohibiting platforms from employing 'dark patterns'—deceptive practices designed to complicate actions such as cancelling subscriptions or opting out of services (DSA, art. 25). Similarly, the EU's AIA prohibits the use of subliminal techniques, such as flashing images or sounds, to influence behaviour. It also restricts the deployment of algorithms that specifically target vulnerable groups, including children and the elderly, based on their membership in those groups (AIA, art. 5(1)(a)–(c)). While these provisions address particular harmful practices, they do not fundamentally challenge the broader conception of agency as an individual, possessive characteristic.

Rather, these laws narrowly focus on identifying discrete actions—such as concealing cancellation options, using subliminal messaging, or designing algorithms to manipulate specific groups—that might undermine individual agency. These measures are designed to safeguard and preserve that agency, rather than to reframe or contest its foundational position. Far from undermining the assumption of agency as an internal possession, these laws underscore its centrality by targeting specific, deliberate actions that could erode it. In this sense, they exemplify the extent to which current regulatory frameworks are committed to protecting the liberal, individualistic conception of possessive agency.

My contention is that this same logic applies to the way various laws—whether the GDPR, OSA, DSA, or the AIA—focus specifically on children and minors as a distinct group deserving special protection (GDPR, recitals 38, 49 and art. 8; OSA, §§ 12, 29, 35–37, 53, 60–61; DSA, recitals 46–47, 71, 104 and art. 28; AIA, recital 13 and art. 5(1)(b)). The explicit identification of children as requiring unique safeguards, while presuming that other users possess a fully developed internal agency, reinforces the foundational assumption that agency is an inherent, individual characteristic.

The classification of children and minors as necessitating special protection does not contest the broader idea of agency as an internal possession. Instead, it reinforces this notion by framing children as temporary exceptions to the general rule. These laws operate under the implicit assumption that children, due to their age and developmental stage, have not yet attained the condition of autonomy attributed to adults. Consequently, the protections afforded to children and minors are presented as provisional, functioning as interim measures until they 'graduate' into the generalised condition of possessing full, self-contained agency.

By establishing this category of special protection, the laws, in effect, underscore the notion that the majority of users—those who are not children or minors—are presumed to be fully capable of exercising their agency and safeguarding themselves. In this way, these laws do not fundamentally challenge the conceptual foundations of possessive agency. Instead, they reinforce it by delineating narrow exceptions that merely highlight the presumed autonomy of the majority population. This preserves the status quo, suggesting that the majority of users are not vulnerable precisely because they are assumed to already possess the internal capacity for autonomous decision-making. However, this assumption fails to account for the extent to which algorithmic systems, particularly those relying on deep neural networks, reinforcement learning, and multi-armed bandits, systematically erode the conditions necessary for meaningful autonomy. These systems are designed to eliminate randomness in individual behaviour, refining their predictive accuracy to such a degree that the user's capacity for independent choice becomes entangled with and, in some cases, subordinated to algorithmic optimisations. In this sense, users are not simply exercising autonomy within these systems; rather, they are increasingly consenting—whether knowingly or not—to a mode of intra-action where their agency is pre-structured by the system's capacity to predict and direct their choices. This raises fundamental questions about whether decision-making autonomy, as traditionally conceived, remains sustainable when user behaviour is not only anticipated with near-perfect accuracy but also guided by algorithmic architectures that shape both the perception and experience of choice itself.

To reiterate and clarify, all of these laws are fundamentally grounded in the premise that agency is an inherent characteristic within the individual, conceptualised as an internal property. They also presume a distinct separation between users and platforms, treating platforms as external tools devoid of the capacity to co-constitute or reshape user agency. Under this framework, there is an implicit binary view of agency: it is either something users possess—such as in the general population, with children being a temporary exception—or something users are deprived of due to clear and deliberate acts of deception, such as the use of dark patterns or subliminal messaging, or because they are specifically targeted as members of a vulnerable group.

This binary understanding extends beyond agency to encompass power, which is conceptualised as either explicitly present and exercised through external coercive acts (e.g., deceptive practices or deliberate targeting) or absent in all other situations where such overt mechanisms are not evident. This rigid framing precludes any recognition of the relational dynamics between platforms and users, where agency is not a fixed possession but something co-constituted through their intra-actions.

9. The limits of possessive agency in light of the transformative and directive power of modern recommendation systems

This brings me to the question of why this issue matters—not just why it is important, but why it poses a specific problem for the law and what role, if any, the law can play in addressing it. I understand that one could interpret what I have argued so far as simply pointing out comparative differences without significant consequences or harms that require legal intervention. In other words, why should it fundamentally matter that these laws conceptualise agency as a possessive characteristic within the individual, rather than recognising the person—their subjectivity—as something co-constituted with the platform?

This is important for several reasons. The first and most significant reason is that by adopting the assumptions underpinning these laws, we fail to account for one of the most significant and transformative forms of directive and constitutive power to have emerged in the last decade: the use of deep neural networks, vast computational assemblages, sophisticated algorithms, and predictive models. These systems, through their immense scale and reliance on the law of large numbers, have achieved a level of precision where the gap between their predictions and actual user behaviour is now negligible. This extraordinary asymmetry of power, created and sustained by these systems, is being excluded from the legal and regulatory conversation. What I am suggesting here is that by treating these systems as neutral, inert tools—akin to a hammer that exists 'over there,' entirely distinct and separate from those entangled with its workings—we obscure the reality of their immense intra-active, diffractive, and interstitial force.

That is to say, when systems leveraging deep neural networks, scaling laws and the law of large numbers, and multi-armed bandits and reinforcement learning achieve the ability to 'predict' with potentially over 90% accuracy what will keep us engaged—even without direct data about our behaviour—and where the gap between prediction and actual behaviour is negligible or confined to rare outliers, we are no longer observing 'prediction' in the traditional sense (Révész 2014, Covington *et al.* 2016, Zhang *et al.* 2024). These systems, in effect, guide and direct our actions with such extraordinary precision that it becomes inadequate to use the language of prediction or to frame this phenomenon through the lens of individual agency. What we are encountering here is something fundamentally different in its constitutive power—an intra-active unfolding and an interstitial force that exists neither solely within us nor entirely within the system. Instead, it occupies a distinct and immensely powerful space due to its properties as an emergent, entangled, and relational phenomenon.

This force does not arise from intention, individual action, or internal states but emerges as a relational effect—a dynamic unfolding of these entanglements. It represents a distinct form of intra-action that demands a radical rethinking of the foundational assumptions traditionally held in law about choice, autonomy, and decision-making. Indeed, it challenges the very concept of legal subjectivity—the notion of what it means to be a legal subject—and compels us to reconsider how current applicable laws (e.g., GDPR, OSA, DSA, AIA) imagine and construct legal subjects in the first place.

By this, I mean that if we now have intentionality functioning within the margins of statistical error and agency (Révész 2014, Covington *et al.* 2016, Zhang *et al.* 2024) as a force that operates not at the individual level but at an aggregate level—while simultaneously generating the experience of individual agency (Covington *et al.* 2016, Zhou *et al.* 2020, Adomavicius *et al.* 2021, Wang *et al.* 2021)—then who, exactly, is the legal subject the law assumes it is addressing? When we are operating within such fluid intersections, fragmented points of agential action, and exceedingly narrow scales of influence, how does the law define or conceptualise the entity that is deciding and making decisions in such a context?

If individual action—or, for that matter, the individual *per se*—within a recommendation system is treated as noise (Conti *et al.* 2018, Xin *et al.* 2023), in the sense that prediction does not operate at the level of the individual but only makes sense as a relational, aggregate phenomenon, then the role of the individual becomes fundamentally redefined. In this context, the individual is not irrelevant but gains significance only by virtue of their relation to massive training datasets, algorithmic weights, and distributed and parallel reinforcement learning processes that occur synchronously and simultaneously at both individual and collective levels (Covington *et al.* 2016, Zou *et al.* 2019, Sharma *et al.* 2021, Stamenkovic *et al.* 2022, Feng 2024).

This raises an important question: in what way, and where, can we locate any space for possessive agency? If actions within such a system derive their meaning and significance solely from relational positionality—a phenomenon shaped by entanglement and intra-action rather than autonomous intent (Dillen 2018, Verlie 2020, Harris 2021)—then the existing conception of agency as something inherently owned or possessed by the individual is fundamentally destabilised (Mackenzie and Stoljar 2000, Nedelsky 2011, Stoljar and Mackenzie 2022).

10. The perils of algorithmic influence: Vulnerabilities and high-stakes outcomes

However, my concern, in this context, is not that algorithmic systems are inherently harmful or that their generative capacities are always negative, *per se*. In many cases—education, skill acquisition, entertainment, such as learning new languages, mastering technical skills, discovering creative outlets, or accessing entertainment, such as music—these systems can provide immense value. My concern is about when the significant directive power of modern algorithmic systems and the distributed, emergent, co-constituted agency they generate operates in high-stake contexts where users are vulnerable.

One such context is mental health crises where users may be struggling with depression, anxiety, grief, or other acute mental health conditions (Gibson 2016, Sangeorzan *et al.* 2019, Raj *et al.* 2022). I am also deeply concerned about those in isolation or facing marginalisation—that is, individuals disconnected from support networks or seeking validation and connection (Belfort and Miller 2018, Woloshyn and Savage 2020, Moss *et al.* 2023, Monks-Woods *et al.* 2024). Additionally, and more generally, I have in mind those in states of desperation, by which I mean circumstances marked by heightened uncertainty (e.g., where outcomes are unpredictable or unknown, leaving individuals in a state of anxiety and cognitive overload) and emotional distress, and a pressing need for resolution, whether due to financial instability, medical crises, personal loss, or other complex life challenges that narrow cognitive options (e.g., reducing the ability to critically assess choices, deliberate rationally, or explore alternative courses of action due to mental or emotional strain) and, thus, heighten susceptibility to influence (Cuthbert *et al.* 2003, Verhoeven *et al.* 2011, Lang 2019, Keles *et al.* 2020).

The concern I have is that the types of questions, information, or guidance sought by individuals in vulnerable contexts via these platforms are often open-ended (e.g., questions about meaning, purpose, coping mechanisms, or solutions to complex emotional, social, or practical challenges without a single definitive answer) (Ruiz-

Gómez 2019, Vega 2023, Ng *et al.* 2024), with multiple and diverse potential pathways that a recommendation engine could present (Lavorgna *et al.* 2018, Gupta *et al.* 2020, Hayes and Ben-Shmuel 2024).

These trajectories can be deeply constitutive—shaping their worldview, decisions, and significant life outcomes, such as whether to reconcile or sever ties with a partner after a relationship breakdown, whether to continue or discontinue mental health medications, or how to navigate feelings of profound loss or existential uncertainty (Sangeorzan *et al.* 2019, Raj *et al.* 2022, Moss *et al.* 2023). For example, a user grappling with the collapse of their marriage might encounter content ranging from constructive advice by licensed therapists to misleading guidance from self-proclaimed relationship 'gurus' who exploit their emotional vulnerability (Baker and Rojek 2020, Martaningrat and Kurniawan 2024). Such trajectories might lead them to radical ideologies about gender roles, 'toxic' narratives that blame one partner entirely, or even predatory communities offering oversimplified fixes for complex personal issues (Närvänen *et al.* 2020, Aw and Chuah 2021).

In another case, a user questioning whether to take prescribed medication for depression might be directed to supportive, evidence-based medical advice—or, conversely, to anti-psychiatry communities, conspiracy theories, or alternative remedies that promote unregulated or potentially harmful treatments. Such content might encourage the user to abandon clinically recommended care in favour of pseudoscientific practices, unproven herbal supplements, or extreme dietary regimens, which could exacerbate their condition, lead to financial exploitation, or even pose serious health risks if critical symptoms are left untreated or mismanaged (Vega 2023, Guo *et al.* 2024, Ng *et al.* 2024). Similarly, those wrestling with grief or searching for purpose could be guided toward either constructive spiritual or therapeutic content or exploitative influencers offering pseudoscientific solutions or radical ideologies presented as empowerment—such as narratives promoting extreme self-reliance, fatalistic worldviews that discourage seeking help, conspiracy-laden spiritual practices, or insular communities that frame personal struggles as evidence of higher purpose while isolating individuals from external support (Lavorgna *et al.* 2018, Gupta *et al.* 2020, Heřmanová 2022, Lawrence 2022, Balishyan and Kompatsiaris 2023, Parciack 2023, Monks-Woods *et al.* 2024).

My contention is that the significant risk for individuals in such vulnerable conditions arises from the confluence of multiple interdependent factors, each exerting a disproportionate influence on their susceptibility to harmful pathways. In these contexts, modern recommendation systems can rely on a powerful combination of directive and exploratory powers (e.g., multi-armed bandits, reinforcement learning, deep neural networks, algorithmic weighting of engagement metrics, large-scale training datasets, and predictive modelling techniques), calibrated to maximise engagement by dynamically adapting to the user's emotional, cognitive, and behavioural signals. For someone grappling with acute mental health challenges, each variable—such as the severity of emotional distress, the degree of isolation, the urgency of resolving uncertainty, or the precision of algorithmic predictions—acts as a weighted force, amplifying their influence on the system's outputs. For instance, high emotional distress carries significant weight, intensifying the user's focus on content that promises immediate resolution or validation, regardless of its accuracy or long-term implications.

At the same time, the system's ability to continuously refine its recommendations based on exploratory strategies means that even marginal signals—such as prolonged pauses on specific content—can be magnified and incorporated into its decision-making. The intersection of these forces can generate feedback loops, where the algorithm not only detects and reinforces the user's vulnerabilities but also amplifies them by steering them—through exploratory techniques such as multi-armed bandits testing various content combinations, reinforcement learning optimising for engagement metrics, and contextual fine-tuning based on implicit signals like watch time, scrolling behaviour, and interaction patterns—toward highly engaging yet potentially harmful trajectories.

This relational entanglement between user vulnerability and algorithmic precision means that risks are not additive but multiplicative (i.e., the various factors—such as user emotional state, algorithmic exploratory techniques, and the dynamic fine-tuning of content rankings—do not merely stack their effects linearly but instead interact in ways that exponentially amplify the impact of each, creating a compounded and deeply entangled influence on user behaviour). The system's immense computational capacity is capable of turning isolated signals into deeply constitutive pathways. The result is a context where harm emerges not from a single variable but from the complex, dynamic entanglement of all contributing factors that constitute a gravitational pull, or distributed and co-constituted agency, so powerful that users—particularly those in vulnerable contexts or conditions marked by heightened emotional distress, cognitive overload, or desperation—find it nearly impossible to resist. By this, I mean that the directive pull of these systems, driven by scaling laws and the laws of large numbers, operates with such precision that individual variability becomes statistically negligible. This enables the system to create pathways that *feel* intuitively inevitable by aligning user behaviour so closely with algorithmic predictions that the sense of agency is effectively absorbed into the system's optimisation processes.

11. Conclusion

The key question for legal scholars and those interested in algorithmic governance is this: at a fundamental level, what is this distinct form of agency that the law must now contend with, and how does it differ from how agency has traditionally been conceived in legal frameworks? Further, what are the limitations and potentialities of the law in addressing the unique harms that may arise when agency—the capacity to act—is so deeply co-constitutive and relational?

An immediate response might suggest increased transparency and disclosure as a solution. However, this approach is fundamentally limited in this context. The co-constitutive, intra-active, and interstitial nature of the directive power we are concerned with is emergent and diffractive; it is not something that can be neatly articulated or fixed in a clear description. The complexity and sophistication of these systems, particularly those driven by deep neural networks, defy simple models of transparency. These systems do not operate through rigid, rule-based mechanisms (e.g., "if X, then do Y") but rather through probabilistic logics, patterns of aggregate behaviour, and the dynamics of machine learning. Consequently, there is no static process or mechanism to disclose; instead, there is a directive effect that emerges as a product of these relational and interactive dynamics.

Focusing exclusively on transparency or disclosure risks reinforcing the very problematic assumptions underpinning current law—such as those embodied in the GDPR, OSA, and DSA—grounded in a possessive, individualistic understanding of agency that treat it as something internal to the individual. By prioritising transparency, we risk obscuring and, in effect, perpetuating this problematic assumption. The problem, as I see it, lies in recognising that the form of agency at play here is not individual or internal but fundamentally relational, distributed, and emergent. Any attempt to address these systems solely through transparency risks misdiagnosing the nature of the issue and, so, fail to engage with a material, contributory source of the harm.

This brings us to a broader question: why should this even be considered a legal problem? My response is twofold. First, we must not view this distinct form of agency as something that exists outside of law. Rather, it is an effect of the constitutive power of law itself. By this, I mean that this emergent, interstitial form of directive power arises because of the specific ways law conceptualises and regulates agency. The legal focus on individual, possessive agency creates the very conditions under which this relational and directive power can emerge and operate. In other words, this is not a problem resulting from the absence of law but from the particular ontological framing and assumptions embedded in the law.

Secondly, and relatedly, law, as Judith Butler has argued (drawing on Foucault's concept of the dispositif), is not merely coercive or restrictive (Butler 1989, 1990). It is also productive and generative, shaping the subjects, objects, and relationships it seeks to govern. Thus, this issue is not external to law but is, in fact, a product of legal thinking. This recognition invites a shift in focus: rather than asking whether this is a problem for law, we should be asking how law should configure and constitute its subjects, objects, and relationships in this context (Foucault 1971, Foucault and Sheridan 1972, Butler 1989, Munro 2003, Hartsock 2013). Should the current relational configurations be left unexamined, with directive and constitutive power operating as it does now? Or is there space to imagine and implement a different mode of thinking about and regulating these relationships?

While I do not claim to have easy or definitive answers, it is imperative to re-examine the foundational ontological frameworks of agency that underpin current legal systems. Laws such as the OSA, DSA, GDPR, and AIA are all grounded in a possessive, individualistic conception of agency. We need to explore the possibilities of moving beyond this framing towards a relational, intra-active, and diffractive understanding of agency and power. Such a shift would enable us to reconsider how law conceptualises its subjects, objects, and mechanisms of governance in this context, not as fixed entities but as fluid and dynamic processes that shape and reshape autonomy in real-time. If we were to view autonomy as something that fluctuates in the motion between prediction and action—rather than as a static possession—this would require legal frameworks to acknowledge that users do not merely act upon platforms but are, in turn, acted upon in ways that condition, expand, or constrain their ability to choose. The legal subject would need to be re-imagined as existing within this motion, with autonomy being neither fully present nor entirely absent but instead dynamically negotiated at the intersection of user engagement and algorithmic inference. By recognising this, we could begin to develop regulatory models that do not merely assume an individual's agency as a given but instead account for the shifting and emergent nature of autonomy within algorithmic environments.This re-imagining is especially urgent given the increasing power of algorithmic systems. The capabilities of deep neural networks are being augmented and expanded through technologies like large language models, generative AI, and transformer-based architectures. These advancements are already being integrated into recommendation systems—YouTube, for instance, has begun experimenting with these technologies (Zhang *et al.* 2024). As these systems mature, their directive and constitutive power will likely become even more pronounced, leveraging and intensifying the effects of deep neural networks, multi-armed bandits, individual and collective reinforcement learning, and the law of large numbers. That is, the gap between what these systems predict and what users actually do is going to get even narrower and more negligible in ways that further increase the potential of the system to direct and co-constitute user subjectivity.

In light of these developments, it is important to move beyond the possessive, individualistic understanding of agency that dominates current legal frameworks. Instead, we must focus on the emergent, interstitial, and distributed forms of agency that these systems generate. This is not merely a short-term issue; it represents a long-term challenge that will only grow more significant as these technologies continue to evolve. Addressing this requires a fundamental rethinking of how law imagines and configures its subjects, objects, and relationships in the attention, platform, and surveillance economy.

References

Adomavicius, G., *et al.*, 2021. Context-aware recommender systems: From foundations to recent developments. *In:* F. Ricci, L. Rokach and B. Shapira, eds., *Recommender Systems Handbook* [online]. Cham: Springer, 211–250. Available at: https://doi.org/10.1007/978-1-0716-2197-4_6

Alaimo, S., and Hekman, S.J., 2008. *Material Feminisms.* Bloomington: Indiana University Press.

Alter, A., 2017. *Irresistible: The rise of addictive technology and the business of keeping us hooked.* London: Penguin Press.

Aw, E.C.X., and Chuah, S.H.W., 2021. "Stop the unattainable ideal for an ordinary me!" fostering parasocial relationships with social media influencers: The role of self-discrepancy. *Journal of Business Research* [online], 132, 146–157. Available at: https://doi.org/10.1016/j.jbusres.2021.04.025

Baker, S.A., and Rojek, C., 2020. *Lifestyle gurus: Constructing authority and influence online.* Hoboken: John Wiley & Sons.

Balishyan, S., and Kompatsiaris, P., 2023. Platform Spiritualities: Entrepreneurial Selves and Post-Feminist Sensibilities of Russian Influencers. *Observatorio (OBS*)* [online], 17(5). Available at: https://doi.org/10.15847/obsOBS17520232420

Barad, K., 2003. Posthumanist performativity: Toward an understanding of how matter comes to matter. *Signs: Journal of Women in Culture and Society* [online], 28(3), 801–831. Available at: https://doi.org/10.1086/345321

Barad, K., 2007. *Meeting the Universe Halfway: Quantum Physics and the Entanglement of Matter and Meaning* [online]. Durham: Duke University Press. Available at: https://doi.org/10.2307/j.ctv12101zq

Barad, K., 2014. Diffracting Diffraction: Cutting Together-Apart. *Parallax* [online], 20(3), 168–187. Available at: https://doi.org/10.1080/13534645.2014.927623

Barclay, L., 2000. Autonomy and the Social Self. *In:* C. Mackenzie and N. Stoljar, eds., *Relational Autonomy: Feminist Perspectives on Autonomy, Agency, and the Social Self* [online]. New York: Oxford University Press USA. Available at: https://doi.org/10.1093/oso/9780195123333.003.0003

Belfort, E.L., and Miller, L., 2018. Relationship between adolescent suicidality, self-injury, and media habits. *Child and Adolescent Psychiatric Clinics* [online], 27(2), 159–169. Available at: https://doi.org/10.1016/j.chc.2017.11.004

Bennett, J., 2004. The force of things: Steps toward an ecology of matter. *Political Theory* [online], 32(3), 347–372. Available at: https://doi.org/10.1177/0090591703260853

Benson, P., 2014. Feminist Commitments and Relational Autonomy. *In:* A. Veltman and M. Piper, eds., *Autonomy, Oppression, and Gender* [online]. Oxford University Press. Available at: https://doi.org/10.1093/acprof:oso/9780199969104.003.0005

Bergsdóttir, A., 2017. Cyborgian entanglements: post-human feminism, diffraction and the science exhibition Bundled-up in Blue. *Museum Management and Curatorship* [online], 32(2), 108–122. Available at: https://doi.org/10.1080/09647775.2017.1284018

Bozalek, V., and Zembylas, M., 2017. Diffraction or reflection? Sketching the contours of two methodologies in educational research. *International Journal of Qualitative Studies in Education* [online], 30(2), 111–127. Available at: https://doi.org/10.1080/09518398.2016.1201166

Brown, M.A., *et al.*, 2022. Echo chambers, rabbit holes, and algorithmic bias: How YouTube recommends content to real users. *SSRN* [online], 4114905. Available at: https://doi.org/10.2139/ssrn.4114905

Butler, J., 1989. Foucault and the Paradox of Bodily Inscriptions. *The Journal of Philosophy* [online], 86(11), 601–607. Available at: https://doi.org/10.5840/jphil198986117

Butler, J., 1990. *Gender Trouble: Feminism and the Subversion of Identity.* New York: Routledge.

Chen, Z., *et al.*, 2024. Data Scarcity in Recommendation Systems: A Survey. *ACM Transactions on Recommender Systems* [online], 3(3). Available at: https://doi.org/10.1145/3639063

Conti, E., *et al.*, 2018. Improving exploration in evolution strategies for deep reinforcement learning via a population of novelty-seeking agents. *Advances in Neural Information Processing Systems* [online], 31. Available at: https://arxiv.org/abs/1712.06560

Covington, P., Adams, J., and Sargin, E., 2016. Deep neural networks for YouTube recommendations. *Proceedings of the 10th ACM Conference on Recommender Systems* [online], 191–198. Available at: https://doi.org/10.1145/2959100.2959190

Cuthbert, B.N., *et al.*, 2003. The psychophysiology of anxiety disorder: Fear memory imagery. *Psychophysiology* [online], 40(3), 407–422. Available at: https://doi.org/10.1111/1469-8986.00043

Dillen, M., 2018. *Time to (intra-) act* [online]. Available at: http://hdl.handle.net/2105/43543

Downie, J., and Llewellyn, J.J., 2011. *Being Relational: Reflections on Relational Theory and Health Law* [online]. Vancouver: UBC Press. Available at: https://doi.org/10.59962/9780774821902

Draude, C., 2020. Boundaries Do Not Sit Still from Interaction to Agential Intra-action in HCI. *In:* M. Kurosu, ed., *Human-Computer Interaction. Design and User Experience: Thematic Area, HCI 2020, Held as Part of the 22nd International Conference, HCII 2020* [online]. Copenhagen: Springer International, 20–32. Available at: https://doi.org/10.1007/978-3-030-49059-1_2

Elbanna, A., 2018. Making a Difference in ICT research: Feminist theorization of sociomateriality and the diffraction methodology. *In:* U. Schultze *et al.*, eds., *Living with Monsters? Social Implications of Algorithmic Phenomena, Hybrid Agency, and the Performativity of Technology: IFIP WG 8.2 Working Conference on the Interaction of Information Systems and the Organization, IS&O 2018, San Francisco, CA, USA, December 11-12, 2018, Proceedings* [online]. Springer, 140–155. Available at: https://doi.org/10.1007/978-3-030-04091-8_11

Elwood, S., and Leszczynski, A., 2018. Feminist digital geographies. *Gender, Place & Culture* [online], 25(5), 629–644. Available at: https://doi.org/10.1080/0966369X.2018.1465396

Fang, H., *et al.*, 2020. Deep learning for sequential recommendation: Algorithms, influential factors, and evaluations. *ACM Transactions on Information Systems (TOIS)* [online], 39(1), 1–42. Available at: https://doi.org/10.1145/3426723

Feng, M., 2024. A Analytical and Practical Insights into Multi-Armed Bandit Problems in Recommendation Systems. *Highlights in Science, Engineering and Technology* [online], 94, 211–216. Available at: https://doi.org/10.54097/tg7bpm76

Feniak, H., 2021. Intra-action: Barad's "agential realism" and modernism. *In:* V. Prakash, M. Casciato and D.E. Coslett, eds., *Rethinking Global Modernism* [online]. London: Routledge, 120–131. Available at: https://doi.org/10.4324/9781003120209-10

Fogg, B., 2009. A behavior model for persuasive design. *Proceedings of the 4th International Conference on Persuasive Technology* [online]. New York: Association for Computing Machinery, 1–7. Available at: https://doi.org/10.1145/1541948.1541999

Foucault, M., 1971. *The order of things: An archaeology of the human sciences*. New York: Vintage Books.

Foucault, M., and Sheridan, A., 1972. *The archaeology of knowledge ; and, The discourse on language.* New York: Pantheon Books.

Gao, L., *et al.*, 2017. Learning in high-dimensional multimedia data: the state of the art. *Multimedia Systems* [online], 23, 303–313. Available at: https://doi.org/10.1007/s00530-015-0494-1

Georgevici, A.I., and Terblanche, M., 2019. Neural networks and deep learning: a brief introduction. *Intensive Care Medicine* [online], 45(5), 712–714. Available at: https://doi.org/10.1007/s00134-019-05537-w

Gibson, M., 2016. YouTube and bereavement vlogging: Emotional exchange between strangers. *Journal of Sociology* [online], 52(4), 631–645. Available at: https://doi.org/10.1177/1440783315573613

Guo, Z., Simpson, E., and Bernardi, R., 2024. Medfluencer: A Network Representation of Medical Influencers' Identities and Discourse on Social Media. *arXiv preprint* [online], arXiv:2407.05198. Available at: https://doi.org/10.48550/arXiv.2407.05198

Gupta, N., *et al.*, 2020. The plastic surgery social media influencer: ethical considerations and a literature review. *Aesthetic Surgery Journal* [online], 40(6), 691–699. Available at: https://doi.org/10.1093/asj/sjz329

Harris, D., 2021. *Karen Barad's feminist materialism: Intra-action and diffraction.* Cambridge Scholars.

Hartsock, N., 2013. Foucault on power: a theory for women? *In:* L. Nicholson, ed., *Feminism/postmodernism*. London: Routledge, 157–175.

Hayes, A.S., and Ben-Shmuel, A.T., 2024. Under the finfluence: Financial influencers, economic meaning-making and the financialization of digital life. *Economy and Society* [online], 53(3), 478–503. Available at: https://doi.org/10.1080/03085147.2024.2381980

Heřmanová, M., 2022. "We Are in Control": Instagram Influencers and the Proliferation of Conspiracy Narratives in Digital Spaces. *Slovenskỳ národopis* [online], 70(3), 349–368. Available at: https://doi.org/10.31577/SN.2022.3.29

Hollin, G., *et al.*, 2017. (Dis) entangling Barad: Materialisms and ethics. *Social Studies of Science* [online], 47(6), 918–941. Available at: https://doi.org/10.1177/0306312717728344

Hu, G.N., *et al.*, 2018. Collaborative filtering with topic and social latent factors incorporating implicit feedback. *ACM Transactions on Knowledge Discovery from Data (TKDD)* [online], 12(2), 1–30. Available at: https://doi.org/10.1145/3127873

Keles, B., McCrae, N., and Grealish, A., 2020. A systematic review: the influence of social media on depression, anxiety and psychological distress in adolescents. *International Journal of Adolescence and Youth* [online], 25(1), 79–93. Available at: https://doi.org/10.1080/02673843.2019.1590851

Kwa, H.L., Leong Kit, J., and Bouffanais, R., 2022. Balancing collective exploration and exploitation in multi-agent and multi-robot systems: A review. *Frontiers in*

Robotics and AI [online], 8, 771520. Available at: https://doi.org/10.3389/frobt.2021.771520

Lang, P.J., 2019. The cognitive psychophysiology of emotion: Fear and anxiety. *In:* A.H. Tuma and J.D. Maser, eds., *Anxiety and the anxiety disorders* [online]. London: Routledge, 131–170. Available at: https://doi.org/10.4324/9780203728215-10

Lavorgna, L., *et al.*, 2018. Fake news, influencers and health-related professional participation on the Web: A pilot study on a social-network of people with Multiple Sclerosis. *Multiple Sclerosis and Related Disorders* [online], 25, 175–178. Available at: https://doi.org/10.1016/j.msard.2018.07.046

Lawrence, S., 2022. *Digital wellness, health and fitness influencers: Critical perspectives on digital guru media* [online]. London: Taylor & Francis. Available at: https://doi.org/10.4324/9781003256021

Mackenzie, C., 2019. Feminist innovation in philosophy: Relational autonomy and social justice. *Women's Studies International Forum* [online], 72, 144–151. Available at: https://doi.org/10.1016/j.wsif.2018.05.003

Mackenzie, C., and Stoljar, N., eds., 2000. *Relational Autonomy: Feminist Perspectives on Autonomy, Agency, and the Social Self* [online]. Oxford University Press. Available at: https://doi.org/10.1093/oso/9780195123333.001.0001

Martaningrat, N.W.S., and Kurniawan, Y., 2024. The Impact of Financial Influencers, Social Influencers, and FOMO Economy on the Decision-Making of Investment on Millennial Generation and Gen Z of Indonesia. *Journal of Ecohumanism* [online], 3(3), 1319–1335. Available at: https://doi.org/10.62754/joe.v3i3.3604

Mauthner, N.S., 2021. Karen Barad's posthumanist relational ontology: An intra-active approach to theorising and studying family practices. *Families, Relationships and Societies* [online], 10(1), 33–49. Available at: https://doi.org/10.1332/204674321X16111601839112

Monks-Woods, A., Andriopoulou, P., and Grogan, S., 2024. A phenomenological investigation of experiences of people who use YouTube to access support for Borderline Personality Disorder. *Psychological Studies* [online], 69(1), 135–144. Available at: https://doi.org/10.1007/s12646-023-00781-z

Montesinos López, O.A., Montesinos López, A., and Crossa, J., 2022. Fundamentals of artificial neural networks and deep learning. *In:* O.A. Montesinos López, A. Montesinos López and J. Crossa, *Multivariate statistical machine learning methods for genomic prediction* [online]. Cham: Springer, 379–425. Available at: https://doi.org/10.1007/978-3-030-89010-0_10

Morton, T., 2013. Treating objects like women: Feminist ontology and the question of essence. *In:* G. Gaard, S. Estok and S. Oppermann, eds., *International Perspectives in Feminist Ecocriticism* [online]. New York: Routledge, 56–69. Available at: https://doi.org/10.4324/9780203520840-4

Moss, C., Wibberley, C., and Witham, G., 2023. Assessing the impact of Instagram use and deliberate self-harm in adolescents: A scoping review. *International Journal of*

Mental Health Nursing [online], 32(1), 14–29. Available at: https://doi.org/10.1111/inm.13055

Munro, V.E., 2003. On power and domination: feminism and the final Foucault. *European Journal of Political Theory* [online], 2(1), 79–99. Available at: https://doi.org/10.1177/1474885103002001280

Närvänen, E., Kirvesmies, T., and Kahri, E., 2020. Parasocial relationships of Generation Z consumers with social media influencers. *In:* J. Costello and S. Yesiloglu, eds., *Influencer marketing* [online]. London: Routledge, 118–135. Available at: https://doi.org/10.4324/9780429322501-10

Nedelsky, J., 2011. *Law's Relations: A Relational Theory of Self, Autonomy, and Law* [online]. New York: Oxford University Press USA. Available at: https://doi.org/10.1093/acprof:oso/9780195147964.001.0001

Ng, I.K., *et al.*, 2024. The rise of medical influencers: The pros and the cons. *Journal of the Royal College of Physicians of Edinburgh* [online], 54(3), 14782715241261736. Available at: https://doi.org/10.1177/14782715241261736

Parciack, R., 2023. Defeat and glory: Social media, neoliberalism and the transnational tragedy of a divinized baba. *Religions* [online], 14(1), 123. Available at: https://doi.org/10.3390/rel14010123

Raj, R., *et al.*, 2022. Body dysmorphia and social media impact. *International Journal of Health Sciences* [online], 6(S3), 3725–3735. Available at: https://doi.org/10.53730/ijhs.v6nS3.6604

Révész, P., 2014. *The laws of large numbers.* Cambridge, MA: Academic Press.

Rouse, J., 2016. The conceptual and ethical normativity of intra-active phenomena. *Rhizomes: Cultural studies in emerging knowledge* [online], 30 (Quantum Possibilities: The Work of Karen Barad). Available at: https://doi.org/10.20415/rhiz/030.e01

Ruiz-Gómez, A., 2019. Digital Fame and Fortune in the age of Social Media: A Classification of social media influencers. *aDResearch: Revista Internacional de Investigación en Comunicación* [online], (19), 8–29. Available at: https://dialnet.unirioja.es/servlet/articulo?codigo=6785540

Salehi Rizi, F., and Granitzer, M., 2017. Properties of vector embeddings in social networks. *Algorithms* [online], 10(4), 109. Available at: https://doi.org/10.3390/a10040109

Sangeorzan, I., Andriopoulou, P., and Livanou, M., 2019. Exploring the experiences of people vlogging about severe mental illness on YouTube: An interpretative phenomenological analysis. *Journal of Affective Disorders* [online], 246, 422–428. Available at: https://doi.org/10.1016/j.jad.2018.12.119

Sharma, A., Patel, N., and Gupta, R., 2021. Leveraging Reinforcement Learning and Multi-Armed Bandit Algorithms for Real-Time Optimization in Ad Campaign Management. *European Advanced AI Journal* [online], 10(2). Available at: https://eaaij.com/index.php/eaaij/article/view/10

Silva, N., *et al.*, 2022. Multi-armed bandits in recommendation systems: A survey of the state-of-the-art and future directions. *Expert Systems with Applications* [online], 197, 116669. Available at: https://doi.org/10.1016/j.eswa.2022.116669

Smith, B., 2021. How TikTok Reads Your Mind. *The New York Times* [online], 6 Dec. Available at: https://www.nytimes.com/2021/12/05/business/media/tiktok-algorithm.html

Stamenkovic, D., *et al.*, 2022. Choosing the best of both worlds: Diverse and novel recommendations through multi-objective reinforcement learning. *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining* [online], 957–965. Available at: https://doi.org/10.1145/3488560.3498471

Stoljar, N., 2013. Feminist perspectives on autonomy. *Stanford Encyclopedia of Philosophy* [online]. Available at: https://plato.stanford.edu/entries/feminism-autonomy/

Stoljar, N., and Mackenzie, C., 2022. Relational autonomy in feminist bioethics. *In:* W.A. Rogers *et al.*, eds., *The Routledge Handbook of Feminist Bioethics* [online]. New York: Routledge. Available at: https://doi.org/10.4324/9781003016885-7

Sunstein, C., 2018. *# Republic: Divided democracy in the age of social media* [online]. Princeton University Press. Available at: https://doi.org/10.1515/9781400890521

Sunstein, C.R., 2017. A prison of our own design: divided democracy in the age of social media. *Democratic Audit UK* [online], 3 April. Available at: https://www.democraticaudit.com/2017/04/03/a-prison-of-our-own-design-divided-democracy-in-the-age-of-social-media/

Van Wyk, A.R., 2012. What Matters Now? Review of Jane Bennett, Vibrant Matter: A Political Ecology of Things. *Cosmos and History: The Journal of Natural and Social Philosophy* [online], 8(2), 130–137. Available at: https://cosmosandhistory.org/index.php/journal/article/view/302

Vega, R., 2023. *An Influencer Told Me So: Using Advice Response Theory to Understand Health Information on Social Media* [online]. Master's Thesis. San Diego State University. Available at: https://digitalcollections.sdsu.edu/do/b65f1c66-0ee3-4cc7-b6b8-81f5b21e26bd

Verhoeven, F.E., *et al.*, 2011. Clinical and physiological correlates of irritability in depression: results from the Netherlands study of depression and anxiety. *Depression Research and Treatment* [online], 2011(1), 126895. Available at: https://doi.org/10.1155/2011/126895

Verlie, B., 2020. From action to intra-action? Agency, identity and 'goals' in a relational approach to climate change education. *Environmental Education Research* [online], 26(9–10), 1266–1280. https://doi.org/10.1080/13504622.2018.1497147

Vieira, S., *et al.*, 2020. Deep neural networks. *Machine Learning* [online], 2020, 157–172. Available at: https://doi.org/10.1016/B978-0-12-815739-8.00009-2

Wang, X., *et al.*, 2021. Learning intents behind interactions with knowledge graph for recommendation. *Proceedings of the Web Conference* [online], 2021, 878–887. Available at: https://doi.org/10.1145/3442381.3450133

Woloshyn, V., and Savage, M.J., 2020. Features of YouTubeTM videos produced by individuals who self-identify with borderline personality disorder. *Digital Health* [online], 6, 2055207620932336. Available at: https://doi.org/10.1177/2055207620932336

Xin, X., *et al.*, 2023. Improving implicit feedback-based recommendation through multi-behavior alignment. *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval* [online], 932–941. Available at: https://doi.org/10.1145/3539618.3591697

Zhang, G., *et al.*, 2024. Scaling law of large sequential recommendation models. *Proceedings of the 18th ACM Conference on Recommender Systems* [online], 444–453. Available at: https://doi.org/10.1145/3640457.3688129

Zhou, J., *et al.*, 2020. Graph neural networks: A review of methods and applications. *AI open* [online], 1, 57–81. Available at: https://doi.org/10.1016/j.aiopen.2021.01.001

Zou, L., *et al.*, 2019. Reinforcement learning to optimize long-term user engagement in recommender systems. *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* [online], 2810–2818. Available at: https://doi.org/10.1145/3292500.3330668

Zuboff, S., 2019. *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power: Barack Obama's Books of 2019.* London: Profile Books.