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Assembling platform governance as private ordering in the age of generative AI: platform interdependence in policy evolution

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ABSTRACT

The rise of generative AI, such as ChatGPT, has transformed platform governance, affecting not only their own frameworks but also those of interconnected platforms like Twitter/X, TikTok, and Facebook. This study explores the evolution, interdependence, and assembling of platform governance through a comparative analysis of policy documents, including Community Guidelines, Privacy Policies, and Terms of Service. By examining OpenAI's policies alongside those of major social media platforms from 2022 to 2024, we trace the co-evolution of platform values such as privacy, engagement, and accountability. Using longitudinal lexical and time-series analyses, we identify three prominent value patterns: positively-aligned values, divergent values, and floating values. These findings suggest that OpenAI's policy have a significant influence on other platforms, particularly in aligning privacy and accountability while revealing divergences in values such as user choice and platform power. Drawing on assemblage thinking, we argue that governance is an ongoing process contingent on the interplay between heterogeneous entities, where platforms engage in *private ordering* to shape and legitimize their governance structures. The study highlights the interconnectedness of platform governance and the complex ways in which generative AI reshapes policy frameworks across the digital ecosystem. We conclude by reflecting on the implications for both platforms and policymakers, emphasizing the need for coordinated regulation in the face of evolving AI governance.

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Platform governance; policy; generative AI; assemblage; interdependence

Introduction

The rise of generative AI (GenAI) has reshaped their governance frameworks and those of other interconnected platforms and online entities since 2022. This article aims to understand the evolution, assembling, and interdependence of governance frameworks

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– including a platform's Community Guidelines (CG), Privacy Policies (PP), and Terms of Service (TOS) – as they co-constitute GenAI governance. We focus on OpenAI and three major social media platforms – Facebook, Twitter/X, and TikTok – due to their (potential) prominence in the AI industry. An underlying premise is that GenAI is situated within a wider data-driven ecosystem (Van der Vlist et al., 2024). These policies, as forms of discursive performance (Gillespie, 2018), strategically bake certain 'core values' such as community and safety into platform governance (Chan et al., 2025; Scharlach et al., 2024).

Following assemblage thinking (e.g., Deleuze & Guattari, 1987; Latour, 2005; Müller, 2015), particularly as applied within critical policy studies (e.g., Clarke et al., 2015; Ureta, 2014), we investigate the *becoming* process of GenAI (self-)governance. GenAI is not a singular entity, but 'a mode of ordering heterogeneous entities so that they work together for a certain time' (Müller, 2015, p. 28). ChatGPT's governance should not be viewed as predetermined by OpenAI; instead, it is contingent upon the evolving interplay between heterogeneous actants (e.g., social media platforms invested in the AI market). We argue the governance frameworks of OpenAI and major social media platforms reveal what values – which can be understood as ideals governing users' activities (Chan et al., 2025; Scharlach et al., 2024) – get promoted and translated into the assemblage.

We situate the assemblage of GenAI governance within a broader dialogue on platform governance for two reasons. First, platform companies like Meta continue to play a crucial role in shaping both the AI industry and its governance (Widder et al., 2023). Second, AI governance exhibits striking similarities to platform governance, particularly in its emphasis on industry self-regulation (Veale et al., 2023). Platform policies are crafted as infrastructures of 'private ordering' (Belli & Venturini, 2016), defined as 'self-regulation voluntarily undertaken by private parties' through extra-legal means (Elkin-Koren, 2005, p. 376). Private ordering resembles what communication scholars often call 'self-governance' (Gorwa, 2024), but we use private ordering to emphasize the contractual nature of policy documents (Belli & Venturini, 2016) and its similarities with public ordering (Klonick, 2018). Like public ordering, platforms rely on external inputs, including government regulations, media coverage, third-party influences, and users' engagement with content moderation, to revamp their rules (Klonick, 2018; Marchal et al., 2025). As tech companies tweak their policies – sometimes by simply adding terms like 'generative AI' and 'machine learning' (Tan, 2024) – they not only set the terms of interaction between themselves, other companies and users (Gorwa, 2024) but also formalize values and social norms (Chan et al., 2025; Scharlach et al., 2024). These companies form 'a patchwork of governance mechanisms, drawing on a commonly available cultural vocabulary' (Gillespie, 2018, p. 67). Hence, this exploratory study affords opportunities for theorizing the interdependence of social media and AI governance.

We address the following research questions. First, how has OpenAI prescribed and redefined its values through policy documents at both the lexical and discursive levels over time? Platform policies, particularly PP and TOS, are often written in a strategically vague manner to communicate platform values (Scharlach et al., 2024) and insulate platforms from liability (Waldman, 2021). Hence, by systematically analyzing lexical changes within these policies, we can 'trace policy granularity and changes' (Chan et al., 2025, p. 1133), particularly their adaptation and stabilization in response to the emergence of GenAI. The discursive level reveals the contextual meanings embedded in such policies. Second, how have the platform policies – and the values they promote – of major social media platforms co-evolved following the rise of GenAI? Third, how are OpenAI's values interconnected with those of other platforms?

To address these questions, we collected and analyzed publicly-available policy documents from OpenAI, Twitter/X, TikTok, and Facebook between 2022 and 2024 using the WayBack Machine. Informed by previous research on the evolution of platform policies (Chan et al., 2025), we conducted a combination of lexical and content analyses of all policy documents. Then, we performed a series of vector autoregressive (VAR) models and Granger causality tests to examine the interdependence, evolution, and co-evolution of values across platforms. The analyses show (1) the co-evolution of OpenAI's and other platforms' policies at lexical and discursive levels; and (2) three prominent value patterns in the relationship between these policies (i.e., positively-aligned values, divergent values, and floating values). In other words, the value structures prescribed by OpenAI's policies are associated with that of Twitter/X, TikTok, and Facebook. We further contextualize the process of assembling GenAI governance through a close reading of policy changes and relevant news coverage. It aims to provide a more nuanced understanding of the broader governance mechanisms shaping GenAI and its impact on interconnected platforms. We conclude by reflecting on the potential explanations and implications of the co-evolving value patterns, and more broadly, the interdependence of platform governance in the face of GenAI.

Literature review

Interdependence of AI and platform governance

The term 'AI' remains ambiguous, carrying multiple and contested meanings (Crawford, 2021; Suchman, 2023). Suchman (2023) complicates AI as a 'floating signifier' which 'works through a strategic vagueness that serves the interests of its promoters, as those who are uncertain about its referents (popular media commentators, policy makers and publics) are left to assume that others know what it is' (p. 3). The mystification of the magical power of GenAI (Leaver & Srdarov, 2023) overlooks pre-existing biases encoded in large language models like ChatGPT (Bender et al., 2021). Moreover, tech companies like OpenAI and Meta have strategically deployed the rhetoric of openness to lobby for broad regulatory exemptions for 'open source' AI, despite their models not being truly open source (Widder et al., 2023). Alongside ideological constructions, data flows between actors (Cobbe et al., 2023), outsourcing and offshoring practices (Tubaro et al., 2025), and environmental resources (Crawford, 2021) contribute to the production of emerging AI assemblages (Bennani-Taylor, 2024). This study examines how policy documents co-constitute interpretive frames about AI governance.

There have been heated debates on AI governance (Veale et al., 2023). Emerging governance initiatives include legislations by national governments and supranational organizations, international agreements, codes of conduct, and industry self-regulation (Veale et al., 2023). A key challenge is to delimit AI systems as regulatory objects (Ferrari et al., 2023; Veale et al., 2023). It not only arises from the opacity and unpredictability of machine learning (Ferrari et al., 2023) but also the 'many hands' problem in algorithmic supply chains (Cobbe et al., 2023). Indeed, scholars of international political economy have developed the global value chains (GVCs) framework to examine how and why transnational lead firms appropriate, shape, and govern the value creation process across spatially dispersed production networks (Gereffi, 2018). While the GVC approach traditionally focuses on the production of tangible products, scholars have examined the ownership and control of intangible assets like innovation (Rikap, 2024). In the case of AI, lead firms and cloud providers like Amazon and Microsoft offer networked access to AI-as-a-service, enabling smaller companies to utilize pre-trained AI models without building their own infrastructures (Cobbe et al., 2023; Van der Vlist et al., 2024). Model marketplaces such as Hugging Face and GitHub enable users to upload and access AI models, but these intermediaries are often outside the scope of existing regulations (Veale et al., 2023).

These studies highlight the asymmetrical interdependence of various actors within a wider data-driven platform ecosystem. Although tech giants are interdependent on other components of the AI stack (e.g., chipmakers) (Van der Vlist et al., 2024), their corporate ownership and appropriation over knowledge and innovation systems render them intellectual monopolies (Rikap, 2024). Rikap found that Microsoft, Google, Meta, and Amazon assemble and manage their AI corporate innovation networks through distinct techno-economic practices. Tech giants are thus '*systemically important* for the political economy, governance, and accountability of AI' (Cobbe et al., 2023, p. 119; italics original).

These dynamics represent the continuation of tech companies' value extraction practices and platform (self-)governance. Van Dijck (2013) argues that individual social media platforms can be disassembled into distinct microsystems characterized by their techno-cultural dimensions and organized socio-economic structures, whereas 'all platforms combined constitute … the *ecosystem of connective media*' (p. 19; italics original) – a system that engineers and normalizes sociality. There are two central throughlines. First, social media platforms rely on financial, infrastructural, and governance strategies to develop their own microsystems, which in turn increase other complementors' dependence on the platform (Poell et al., 2022). Of particular relevance to this study is what Poell et al. (2022) call 'governance frameworks' which enable platforms to set and justify their private ordering of their microsystems. Second, platforms are organized 'through hierarchical and interdependent layers' (Van Dijck, 2021, p. 2802). Van Dijck's (2021) metaphor of the 'platformization tree' captures how the roots (i.e., digital infrastructures) support the trunk of intermediary platforms and the branches of sectoral application. Social media constitute part of the trunk, channeling data flows between the other layers. As distinct microsystems develop and function as the wider ecosystem, they become 'sensitive to changes in other parts of the ecosystem' (Van Dijck, 2013, p. 19). In this vein, when an intermediary platform modifies its governance framework, other intermediary and sectoral platforms may react to these changes.

Given giant platforms remain key actors in the AI sector (Van der Vlist et al., 2024), it is essential to situate GenAI governance within a wider platform ecosystem. While Van der Vlist et al. (2024) conceptualize AI as an emerging ecosystem comprising infrastructures, models, and applications, we examine the interdependence of GenAI and social media platform governance. As social media serve as important avenues for extracting data to develop and train AI models in the value chains, OpenAI's GenAI models can be seen as an emerging intermediary microsystem. The latter's governance frameworks have the potential to influence those of other intermediary platforms, such as Facebook, Twitter/X, and TikTok, in our study. This research contributes to understanding the co-construction of AI governance through corporate policies.

How platforms govern through private ordering: platform policies as assemblages

Private ordering forms the backbone of corporate power in GVCs (Beckers, 2016; Eller, 2017), and, more recently, platform governance (Belli & Venturini, 2016; Klonick, 2018). Legal scholars have highlighted how corporate codes and customer contracts function as governance instruments (Beckers, 2016; Eller, 2017; Lianos et al., 2024). Reflecting on his experience as general counsel for an interactive media company, Danielsen (2005) demonstrates how the company strategically crafted its online customer contract to align with 'the most consumer-friendly rules in its key markets' as its transnational businesses were 'subject to multiple unclear rules in multiple jurisdictions' (p. 418). In the process of drafting corporate codes, corporations often collaborate with non-governmental organizations and address societal expectations to enhance the legitimacy of private ordering (Beckers, 2016), a trend that we also observe in platform and AI governance (Gorwa, 2024; Veale et al., 2023). As such, private ordering is far from natural legal constructs but deliberately constructed by companies and facilitated by regulatory (in)actions (Beckers, 2016; Danielsen, 2005; Eller, 2017).

Compared to private ordering in traditional GVCs that primarily binds suppliers and employees (Beckers, 2016), platform policies extend their reach to massive user bases. Platforms arguably become the 'new governors' (Klonick, 2018) who exercise corporate power to dictate public rules regarding online speech through platform policies and socio-technical infrastructures for their enforcement (Gillespie, 2018). TOS and PP are typically crafted to protect platforms from legal liability, whereas CG establishes expectations for users regarding appropriate and inappropriate content. Taken together, platform policies are designed to set written rules, build trust with users, and legitimize platform (self-)governance (Gillespie, 2018). For Gillespie, CG performs as a 'gesture' to users, advertisers, and lawmakers, signaling platforms' commitment to moderating content responsibly. Waldman (2021), similarly, writes, 'privacy policies give the impression that the information industry is doing something to protect our data and small, marginal changes after privacy scandals facilitate an escape from greater regulatory oversight' (p. 109).

This study highlights the techno-legal work through which platforms exercise corporate power and reshape private ordering of GenAI. We trace how OpenAI and other platforms convey and formalize underlying governing principles, or 'platform values' (Chan et al., 2025; Scharlach et al., 2024) into the term 'AI' in their policy documents. Previous research showcases social media platforms often selectively (re)articulate values in their evolving policy documents (Chan et al., 2025; Scharlach et al., 2024). For example, while TikTok's community guidelines initially made no reference to authenticity, the revised guidelines mobilized this value to discourage misinformation (Chan et al., 2025). Additionally, Dubois and Reepschlager's (2024) longitudinal analysis of Facebook, Reddit, and Twitter from 2005 to 2020 observed the increased complexity in platforms' policy structures and their definitions of hate speech and harassment. These policies also continuously reframed the responsibility framework, shifting from users alone to including platforms themselves, content moderation tools, and external actors. In the context of GenAI, Edwards et al.'s (2025) examined 13 model providers' Terms and Conditions between January and March 2023. These policies seemed to follow 'a platformisation paradigm,' seeking 'the benefits of neutrality in terms of deferring liability and responsibility to users, while still gaining all the advantages of their position in terms of profit and power' (p. 11). Our intervention is to investigate how OpenAI's policies co-evolve with those of major social media through the lens of platform values.

We adopt assemblage thinking (Anderson et al., 2012; Deleuze & Guattari, 1987; Müller, 2015) to conceptualize platform policies as webs of relations between multiple, heterogeneous entities. Indeed, scholars have suggested viewing AI (e.g., Bennani-Taylor, 2024) and platforms (e.g., Gerrard & Thornham, 2020) as assemblages. Platform policies constitute one of the key elements of such assemblages. Gerrard and Thornham (2020) consider CG of Instagram, Pinterest, and Tumblr as gendered rulebooks that form the broader 'sexist assemblages.' Given the expanding regime of private ordering, it seems crucial to understand the stability and transformation of these assembled orders. Rather than reducing these dynamics to either 'the agential potential of capable agents' or structural social forces, assemblage thinking emphasizes 'both the emergent nature of composition and the relative autonomy of an assemblage's component parts' (Anderson et al., 2012, p. 183). What is at stake are the processes and forms of work through which these heterogeneous entities are temporarily held together (Latour, 2005). Meanwhile, the processes of assembling certain entities and disassembling others (i.e., territorialization and deterritorialization; Deleuze & Guattari, 1987) go hand in hand (Müller, 2015). Studying the evolution of platform policies thus involves examining what is brought into being, what remains stable, and what is displaced. As social media platforms adjust their policies to authorize their own use of user data for AI training (Tan, 2024) while prohibiting unauthorized scraping by others, they actively shape which data practices and relations are brought into being and remain legitimate, and which are displaced.

Conceptualizing platform policies as assemblages opens up opportunities to understand the messy, provisional, and always-in-flux nature of rule-making processes in two ways. First, inspired by theorizations of policy assemblages in critical policy studies (Clarke et al., 2015; Ureta, 2014), it problematizes assumptions that policies result simply from rational choices or are solely determined by a few powerful individuals. Instead, it foregrounds the interdependence between various actors in co-constructing GenAI governance. Second, assemblage thinking takes seriously the performative and relational nature of policies which can be understood 'a way of imagining the world as an object of intervention; as a way of enrolling subjects into a process of acting; and as a practice that seeks to produce effects' (Clarke et al., 2015, p. 34). A policy assemblage begins to assemble when certain issues are translated into policy concerns, followed by the making and enactment of the related policies (Ureta, 2014). Bennani-Taylor (2024) develops the concept of 'discursive infrastructuring' by illustrating how UK national AI policies stabilize the perceived inevitability of AI development, enroll various institutions through policy documents, and translate governmental ambitions into potential policy practices. In the case of platform policies, translation occurs as policies strategically communicate a social world in which governance is necessary, enrolling heterogeneous actors into an array of responsibility and addressing constructed policy problems. Once such relations are stabilized, 'only voices speaking in unison will be heard' (Callon, 1984, p. 223).

With assemblage thinking, we aim to map the interdependencies between OpenAI and other social media microsystems as well as the interplay between stability and dynamism inherent in the becoming of GenAI governance.

Methods and data

We collected and analyzed publicly available policy documents, including CG[1], TOS[2], and PP, from OpenAI, Twitter/X, TikTok, and Facebook between 1 January 2022 and 31 July 2024 using the Wayback Machine (N = 8,516).[3] After cleaning the data and removing duplicates, we compiled a collection of unique documents (N = 232). Each document was tokenized into individual sentences, forming a corpus of separated sentences from the policy documents. To enhance contextual understanding during the coding process, each sentence was merged with the preceding and following sentences, creating a unit of analysis composed of three consecutive sentences (i.e., a section, unique N = 3,741).[4] A 10% sample of these unique sections (N = 375) was randomly selected and prepared for human coding, with the rest reserved for subsequent automated coding. Table 1 summarizes the sample size for each type of policy on the platforms.

Our analytical approach involved three steps. First, a lexical analysis was conducted on the policy documents. Second, we employed an automated coding process using the ChatGPT-4o model, refined with a 10% manually coded dataset, to annotate policy values across all platforms and policy types. Finally, we conducted a series of VAR models and Granger causality tests to explore the temporal influence of values articulated by OpenAI's policies on those of other platforms (Lütkepohl, 2005). We tested whether the lagged values of each coded value in OpenAI's policies predicted the frequency of the same value in the other platforms' policies.

Table 1. Summary of the sample sizes of policy documents across platforms (2022–2024).

	Community Guidelines (CG)	Terms of Service (TOS)	Privacy Policies (PP)
OpenAI			
Snapshots (total)	368	770	160
Snapshots (unique)	15	17	15
Sections (total)	5,825	36,242	5,510
Sections (unique)	92	234	262
Twitter/X			
Snapshots (total)	2,098	499	501
Snapshots (unique)	13	11	14
Sections (total)	32,181	41,484	39,477
Sections (unique)	139	324	486
TikTok			
Snapshots (total)	860	890	210
Snapshots (unique)	13	15	13
Sections (total)	28,075	104,699	12,190
Sections (unique)	349	355	260
Facebook			
Snapshots (total)	279	937	944
Snapshots (unique)	21	48	37
Sections (total)	2,723	57,895	21,160
Sections (unique)	92	637	511

Note: Each section consists of a target sentence combined with the preceding and following sentences to provide contextual understanding.

Lexical analysis

To examine linguistic changes across platforms and policy types, we analyzed each unique document by calculating sentence counts, word frequencies, and unique word counts, excluding punctuation, symbols, numbers, URLs, and special characters. We assessed lexical characteristics related to readability, complexity, and richness. Readability was measured using the Flesch-Kincaid score (Paasche-Orlow et al., 2003), where higher scores indicate more difficult texts. Lexical richness was evaluated using the type-token ratio (TTR), with higher values reflecting greater word diversity, and Hapax richness – the proportion of words appearing only once – was used to gauge complexity (Jockers & Thalken, 2020). This analysis provides a descriptive view of potential co-evolution in policy language after the introduction of ChatGPT.

Content analysis

We conducted a content analysis of policy documents to explore how private ordering is constructed and assembled. Values were coded when they described platform governance or justified promoting specific 'desirable' characteristics of the platform. The codebook was based on previous research on social media platform values (Chan et al., 2025; Scharlach et al., 2024) and further refined through close reading of the related policies. We identified and examined ten values, including power, privacy, safety, choice, community, engagement, protection of intellectual property, improvement, care, and accountability. Each value was defined to clarify its role in representing aspects of governance within the policy documents. While the definitions are mutually exclusive, multiple values could appear in the same section of a policy document. The codebook is presented in Table 2.

Two researchers were trained to use a predefined codebook and independently coded 10% of the sample sections for the presence or absence of each value. They marked

Table 2. Platform values and their operational definitions.

Platform Value	Operational Definition
Power	The degree to which a platform or users can govern content and protect their rights
Privacy	The degree to which users are empowered to manage their personal information, encompassing permissions for data control, sharing, and customization
Safety	The degree to which platform allows or prohibits users from posting to preserve the well-being of users, the platform community, and/or organizations
Choice	The degree to which users are free to pick options that align with their interests (e.g., opt-in/opt-out)
Community	The degree to which a platform values a certain social group characterized by shared practices, communication technologies, and intimate relations
Engagement	The degree to which a platform allows or prohibits interactivity and participation through the platform for certain outcomes
Protection of Intellectual Property	The degree to which a platform establishes rules, guidelines, and mechanisms to safeguard the ownership and rights of creators and organizations over their content, ideas, and digital assets, including prohibiting unauthorized use, distribution, and reproduction
Improvement	The degree to which a platform strives to improve its available features and become central actors of private and public life
Care	The degree to which a platform provides information about support for users and outlines how users can seek help
Accountability	The degree to which a platform or users has a mechanism for holding the platform accountable
No value	The sentence does not contain any values

whether each value was present (1) or absent (0) in randomly selected sections. Intercoder reliability was assessed to evaluate the consistency between the two coders, resulting in an average Krippendorff's α of 0.90 for determining platform values. Sections without values were excluded from further analysis.

Automatic coding. To code the remaining policy sections, we used two approaches based on the value analyzed. For 'Protection of Intellectual Property', 'Care', 'Safety', and 'Choice', we applied the ChatGPT-4o model without fine-tuning, given its strong baseline classification performance (Bommasani et al., 2021). A 10% sample of its outputs was reviewed by human coders, achieving 90% intercoder agreement. Performance metrics were strong: F1 scores of 0.87-0.92, accuracy of 0.89-0.94, precision of 0.88-0.93, and recall of 0.85-0.91. For the remaining values, we fine-tuned models based on GPT-3.5-turbo-0215 to improve performance. Two researchers manually coded 10% of the data to create gold-standard datasets, which were split 70/30 into training and validation sets using a fixed seed. Fine-tuning followed OpenAI's scientific benchmarks, emphasizing diverse samples, clear definitions, and iterative testing (Brown et al., 2020). Data were formatted in JSONL with system prompts, user inputs, and the expected binary outputs (1 = present, 0 = absent). Fine-tuned models performed well, with F1 scores of 0.82-0.88, accuracy of 0.84-0.90, precision of 0.80-0.89, and recall of 0.83-0.87.

VAR and Granger causality analysis

We used Vector Autoregressive (VAR) models and Granger causality tests to assess whether the values articulated in OpenAI's policies influence those of other platforms over time. VAR models (Zivot & Wang, 2006) capture dynamic relationships between multiple time series, enabling us to test whether lagged values of each policy value in OpenAI's documents predict corresponding changes in other platforms' policies. Granger causality tests further determine whether past changes in OpenAI's policies statistically 'cause' future changes elsewhere, based on temporal sequencing.

Temporal dataset. We constructed a time-series dataset covering 1 January 2022–31 July 2024. Each row represents a specific date; each column records the frequency of a particular value annotated in a platform's policy snapshot (by platform and policy type). If a policy remained unchanged on a given date, values were carried forward from the most recent version. To meet the stationarity assumption required for VAR and Granger analysis, we applied the Augmented Dickey-Fuller test (Hamilton, 2020). Some series, such as 'Power' in OpenAI's CG and PP, were initially non-stationary ($p = .12$ and $p = .08$, respectively) and were first-differenced to avoid misleading or spurious regression results (Granger & Newbold, 1974). All transformed series passed stationarity checks ($p < .01$) and were used for further analysis.

Granger causality test. We modeled changes in each platform's policies as a function of lagged changes in OpenAI's CG, TOS, and PP, testing each annotated value separately. For example, to examine whether OpenAI's changes in 'Power' influenced Twitter/X's CG, we tested whether earlier changes in OpenAI's policies predicted later changes in Twitter/X's. The regression model used is specified in the equation below.

$$twitter\_cg_t = \beta_0 + \beta_1 \cdot openai\_cg_{t-1} + \beta_2 \cdot openai\_pp_{t-1} + \beta_3 \cdot openai\_tos_{t-1} + \beta_4 \cdot twitter\_cg_{t-1} + \varepsilon_t$$

Instantaneous causality test. We also conducted instantaneous causality tests to explore whether changes in OpenAI's policies coincided with immediate changes in other platforms' policies. While Granger tests assess predictive influence, instantaneous tests detect synchronous effects. All analyses were conducted using the VAR() and causality() functions from the *vars* package in R.

Findings

We examine the evolution, interdependence, and assembling of values as expressed in policies across OpenAI and major social media platforms at both lexical and discursive levels. We begin by presenting the lexical analysis of OpenAI's policy documents in comparison to those of Twitter/X, TikTok, and Facebook. Second, we demonstrate how the platform values articulated by these social media platforms have been reshaped following the introduction of ChatGPT. Nuanced covariances are observed, revealing the temporal influence of OpenAI's policy changes on other platforms varies depending on the specific values studied.

Lexical characteristics of platform governance frameworks

Across OpenAI and the three platforms, policy documents have generally increased in length over time while exhibiting a decline in lexical diversity and complexity. OpenAI's CG saw a substantial expansion, particularly in early 2024, with a 26.5% increase in word count, while OpenAI's TOS and PP experienced notable growth. These trends are visualized in Figure 1, which illustrates how document length has evolved across platforms and policy types. Figure 2 shows unique word counts increased in most policies, though fluctuations in Twitter/X's and Facebook's TOS suggest periodic content restructuring.

Despite these expansions, readability trends suggest longer policies do not necessarily become more difficult to understand. Figure 3(a) illustrates that OpenAI's CG became easier to read over time, with a decrease in Flesch-Kincaid scores, while other policies showed more mixed readability shifts. Meanwhile, Figure 3(b) indicates a decline in textual richness, as measured by TTR, implying that policies incorporated more repetitive language over time. This pattern aligns with Figure 3(c), which tracks textual complexity

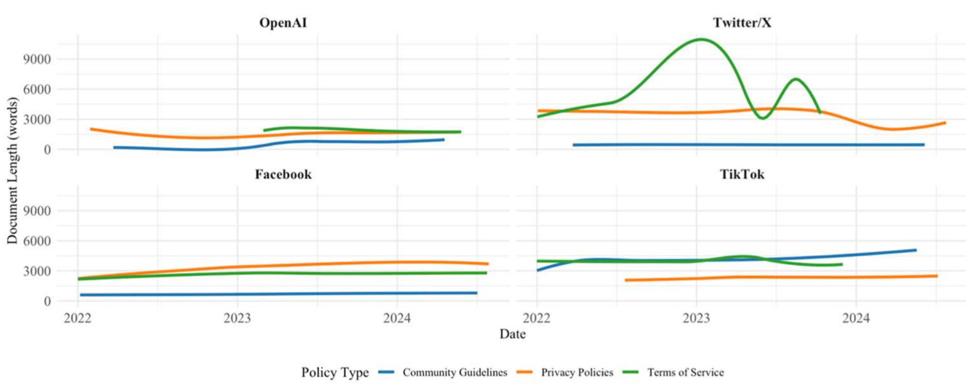

Figure 1. Trends of document length (words) over time by platform and policy type.

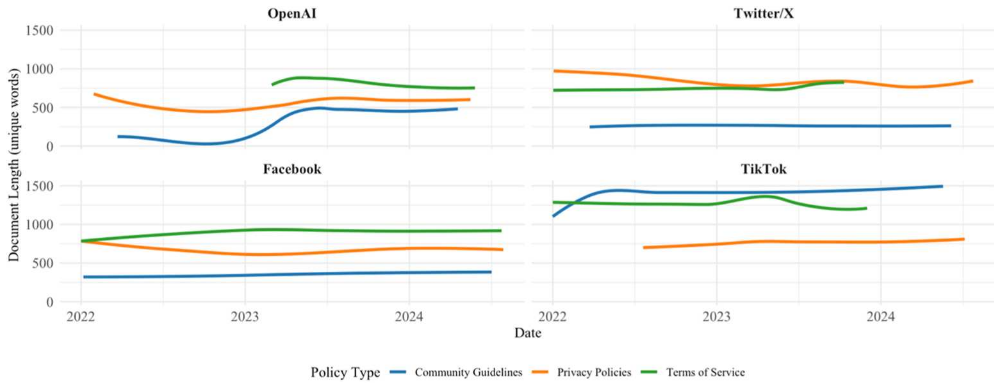

Figure 2. Trends of document length (unique words) over time by platform and policy type.

through Hapax richness, showing a general decrease across OpenAI and social media platforms. As policy documents expanded, they relied on more standardized and recurring terminology.

These findings provide descriptive and contextual understanding about how policy documents evolve structurally over time, complementing our analysis of value co-evolution in the next step. While platforms adapted their policies in response to technological advancements and governance challenges, there is an increasing formalization of policy language (Chan et al., 2025; Dubois & Reepschlager, 2024).

Temporal influence of OpenAI's value frequency changes on social media platforms

Building on these lexical trends, we examine the temporal influence of OpenAI's policy changes on the values articulated in the other platforms' policies. If there is an association between their policy changes, the interdependence of platform governance can be empirically substantiated. This echoes assemblage thinking, which avoids making a priori assumptions about relationships between entities. Granger causality tests were conducted to determine whether lagged changes in OpenAI's CG, PP, and TOS predicted value changes in corresponding policies of the other platforms.[5] The results reveal both significant positive and negative associations across various values and policy types.

Twitter/X. OpenAI's CG had significant positive effects on Twitter/X's privacy value ($\beta = .01$, $p < .001$) and engagement ($\beta = .07$, $p < .001$), while improvement showed a significant negative association ($\beta = -.07$, $p < .001$). Changes in OpenAI's TOS positively predicted the privacy value ($\beta = .01$, $p < .001$), highlighting the influence of OpenAI on Twitter/X's policy documents. In Twitter/X's PP, changes in OpenAI's CG had a significant negative effect on the power value ($\beta = -.02$, $p < .001$), while the choice value was positively associated with OpenAI's CG ($\beta = .17$, $p < .001$). However, the value of choice was negatively influenced by OpenAI's TOS ($\beta = -.04$, $p < .05$). The engagement value in Twitter/X's TOS was significantly predicted by changes in all of OpenAI's policies, with the most notable effect from OpenAI's TOS ($\beta = .20$, $p < .001$). Conversely, choice was negatively impacted by OpenAI's CG ($\beta = -.02$, $p < .05$), PP ($\beta = -.13$, $p < .001$), and TOS ($\beta = -.03$, $p < .001$). Results are summarized in Table 3.

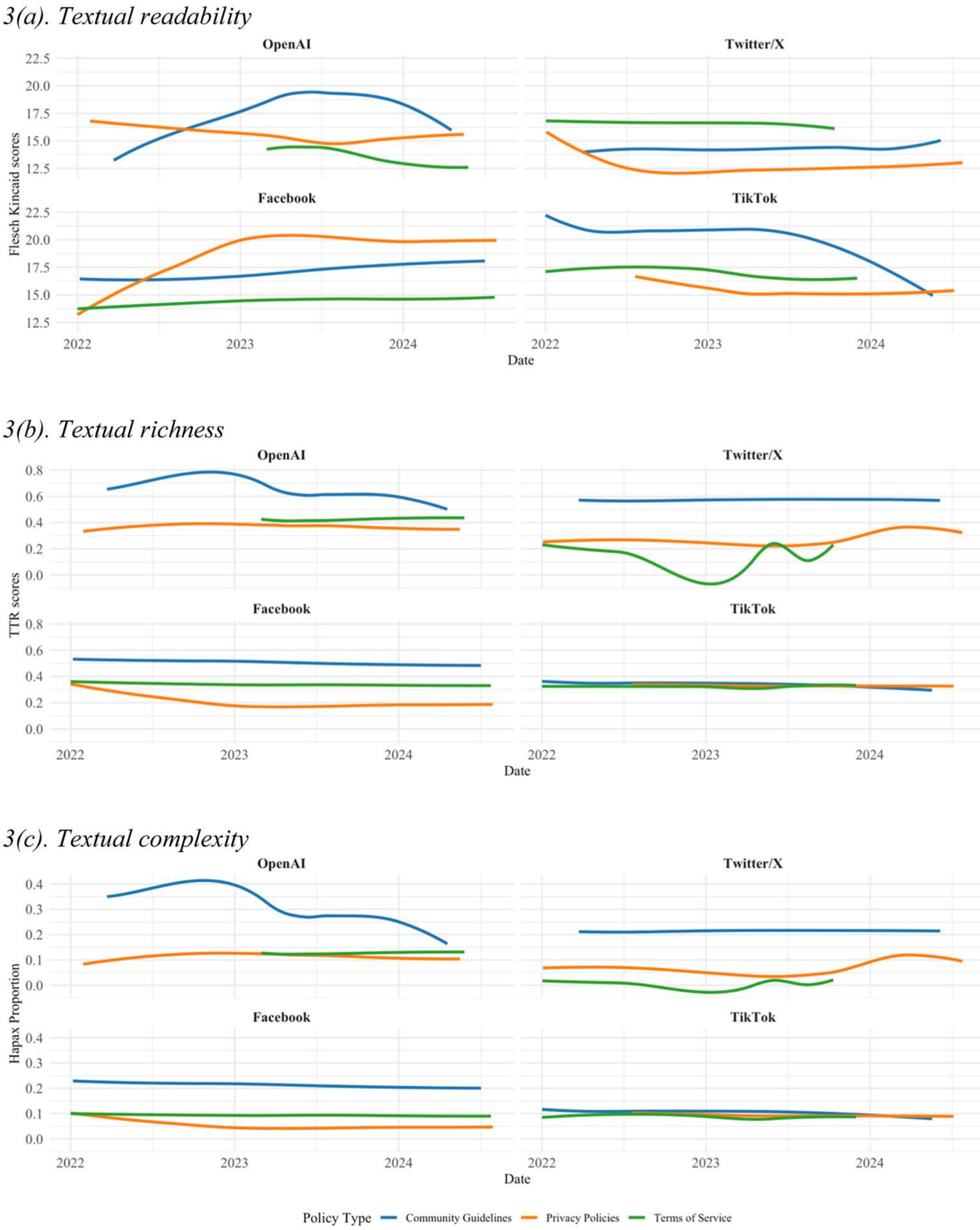

Figure 3. Lexical overview of policy document over time by platform and policy type.

TikTok. For TikTok's CG, changes in OpenAI's PP significantly predicted a negative shift in value of power ($\beta = -.02$, $p < .05$), while engagement was positively influenced by OpenAI's TOS ($\beta = .11$, $p < .001$). The value of privacy was significantly predicted by OpenAI's CG ($\beta = .002$, $p < .05$) and PP ($\beta = .002$, $p < .05$). In TikTok's PP, OpenAI's CG predicted a positive shift in the community value ($\beta = .01$, $p < .05$) and intellectual property protection ($\beta = .01$, $p < .05$). OpenAI's TOS positively influenced the privacy value ($\beta = .004$, $p < .05$). TikTok's TOS showed significant positive effects in response

Table 3. Lagged changes in OpenAI's policies predicting changes in Twitter/X's policies.

Values	OpenAI (Community Guidelines)	OpenAI (Privacy Policy)	OpenAI (Terms of Use)	Lagged DV	Adjusted R^2
Community Guidelines					
Power	NA				
Privacy	.01(.002)***	n.s.	.01(.002)***	.95(.01)***	.92***
Safety	n.s.	n.s.	n.s.	.99(.01)***	.91***
Choice	NA				
Community	NA				
Engagement	.07(.0002)***	n.s.	n.s.	.86(.003)**	.93***
Property	NA				
Improvement	−.07(.002)***	−.002(.001)*	−.005(.001)***	.91(.02)***	.91***
Care	NA				
Accountability	NA				
Privacy Policy					
Power	−.02(.01)***	−.05(.02)*	−.01(.01)*	.94(.01)***	.93***
Privacy	.10(.04)**	n.s.	n.s.	.95(.01)***	.94***
Safety	n.s.	n.s.	n.s.	.96(.01)***	.93***
Choice	.17(.04)***	−.21(.12)*	−.04(.02)*	.96(.01)***	.96***
Community	n.s.	.04(.02)*	n.s.	.92(.01)***	.93***
Engagement	.01(.01)*	n.s.	n.s.	.93(.01)***	.94***
Property	NA				
Improvement	−.04(.01)***	n.s.	n.s.	.94(.01)***	.93***
Care	NA				
Accountability	.01(.002)***	.02(.01)*	n.s.	.92(.01)***	.93***
Terms of Service					
Power	n.s.	n.s.	n.s.	.91(.01)***	.93***
Privacy	n.s.	.05(.01)***	.08(.01)***	.87(.01)***	.90***
Safety	−.01(.003)**	n.s.	n.s.	.93(.01)***	.94***
Choice	−.02(.01)*	−.13(.03)***	−.03(.01)***	.85(.01)***	.88***
Community	.01(.003)*	n.s.	n.s.	.93(.01)***	.93***
Engagement	.004(.001)*	.11(.01)***	.20(.02)***	.76(.01)***	.86***
Property	n.s.	.19(.10)*	.10(.04)*	.92(.01)***	.93***
Improvement	−.01(.004)*	n.s.	n.s.	.93(.01)***	.90***
Care	NA				
Accountability	.02(.01)**	.07(.02)**	.03(.01)*	.95(.01)***	.95***

Note: Unstandardized regression coefficients are presented, with standard errors in parentheses.
NA indicates insufficient data points for temporal causality analysis, while n.s. denotes not statistically significant.
*** $p < .001$, ** $p < .01$, * $p < .05$.

to OpenAI's PP, particularly for the privacy value (β = .01, $p < .05$). However, the choice value was negatively influenced by OpenAI's PP (β = −.05, $p < .05$). The temporal influences of OpenAI's policies on TikTok's policies are illustrated in Table 4.

Facebook. Facebook's CG exhibited significant positive associations with OpenAI's CG for the community value (β = .004, $p < .001$). Conversely, improvement was negatively influenced by changes in OpenAI's PP (β = −.03, $p < .05$) and TOS (β = −.02, $p < .001$). In Facebook's PP, significant positive effects were observed for the privacy value, which was influenced by OpenAI's CG (β = .02, $p < .001$), PP (β = .01, $p < .05$), and TOS (β = .03, $p < .001$). The safety value, however, showed a significant negative impact from OpenAI's CG (β = −.01, $p < .01$) and TOS (β = −.01, $p < .05$). In Facebook's TOS, OpenAI's CG positively predicted the community value (β = .01, $p < .01$), while improvement was negatively affected by OpenAI's PP (β = −.03, $p < .05$). The accountability value exhibited positive associations with OpenAI's CG (β = .02, $p < .01$) and PP (β = .07, $p < .01$). Table 5 summarizes the results of the Granger-caused effects.

Significant Granger-caused influences. Table 6a summarizes the significant positive Granger-caused influences from OpenAI's policy changes on the values of the studied social media platforms. OpenAI's CG and PP demonstrated substantial predictive

Table 4. Lagged changes in OpenAI's policies predicting changes in TikTok's policies.

Values	OpenAI (Community Guidelines)	OpenAI (Privacy Policy)	OpenAI (Terms of Use)	Lagged DV	Adjusted R^2
Community Guidelines					
Power	n.s.	−.02(.01)*	n.s.	.97(.01)***	.94***
Privacy	.002(.001)*	.002(.001)*	n.s.	.94(.01)***	.96***
Safety	−.03(.01)*	n.s.	n.s.	.95(.01)***	.97***
Choice	n.s.	n.s.	.002(.001)*	.94(.01)***	.95***
Community	n.s.	n.s.	n.s.	.97(.004)***	.93***
Engagement	n.s.	n.s.	.11(.03)***	.96(.01)***	.94***
Property	n.s.	n.s.	.001(.004)*	.98(.01)***	.95***
Improvement	n.s.	n.s.	n.s.	.93(.01)***	.92***
Care	NA				
Accountability	n.s.	n.s.	n.s.	.92(.01)***	.95***
Privacy Policy					
Power	−.004(.002)*	n.s.	n.s.	.94(.01)***	.94***
Privacy	n.s.	n.s.	.004(.002)*	.95(.004)***	.92***
Safety	n.s.	n.s.	n.s.	.92(.004)***	.93***
Choice	n.s.	n.s.	n.s.	.96(.002)***	.93***
Community	.01(.01)*	n.s.	n.s.	.91(.004)***	.93***
Engagement	n.s.	n.s.	n.s.	.92(.004)***	.93***
Property	.01(.003)*	n.s.	n.s.	.92(.003)***	.94***
Improvement	n.s.	n.s.	n.s.	.93(.004)***	.92***
Care	NA				
Accountability	n.s.	n.s.	n.s.	.96(.004)***	.93***
Terms of Service					
Power	n.s.	n.s.	n.s.	.92(.01)***	.91***
Privacy	n.s.	n.s.	.01(.003)*	.92(.01)***	.93***
Safety	NA				
Choice	n.s.	−.05(.02)*	−.01(.004)*	.92(.01)***	.93***
Community	n.s.	n.s.	n.s.	.92(.01)***	.94***
Engagement	n.s.	n.s.	n.s.	.95(.01)***	.95***
Property	n.s.	n.s.	n.s.	.94(.01)***	.94***
Improvement	n.s.	n.s.	n.s.	.95(.01)***	.94***
Care	NA				
Accountability	n.s.	n.s.	n.s.	.92(.01)***	.91***

Note: Unstandardized regression coefficients are presented, with standard errors in parentheses.
NA indicates insufficient data points for temporal causality analysis, while n.s. denotes not statistically significant.
*** $p < .001$, ** $p < .01$, * $p < .05$.

influence on values such as privacy, engagement, and accountability in Twitter/X's CG and PP. Privacy and engagement were positively influenced by OpenAI's CG, with accountability showing a positive temporal association under both the CG and PP. Furthermore, OpenAI's PP had a strong positive impact on choice, engagement, and intellectual property values within Twitter/X's PP.

For TikTok, OpenAI's policies exhibited significant positive effects. The privacy, engagement, and intellectual property values in TikTok's CG and PP were positively influenced by OpenAI's PP and TOS. The results indicate the choice value in TikTok's TOS was significantly influenced by OpenAI's PP, suggesting a temporal spillover of privacy-related values from OpenAI to TikTok. Similarly, Facebook's policies showed positive Granger-caused associations, particularly in the values of community, engagement, privacy, and accountability. OpenAI's CG notably influenced community values in Facebook's CG, while privacy and accountability showed strong positive associations across multiple policy types. OpenAI's TOS also influenced privacy and intellectual property values in Facebook's policies, indicating broader value-sharing across platforms.

Table 5. Lagged changes in OpenAI's policies predicting changes in Facebook's policies.

Values	OpenAI (Community Guidelines)	OpenAI (Privacy Policy)	OpenAI (Terms of Use)	Lagged DV	Adjusted R^2
Community Guidelines					
Power	NA				
Privacy	n.s.	n.s.	n.s.	.93(.01)***	.93***
Safety	n.s.	n.s.	n.s.	.95(.01)***	.92***
Choice	NA				
Community	.004(.001)***	n.s.	n.s.	.94(.01)***	.95***
Engagement	NA				
Property	n.s.	n.s.	n.s.	.80(.001)***	.80***
Improvement	n.s.	−.03(.02)*	−.02(.01)***	.87(.01)***	.88***
Care	NA				
Accountability	NA				
Privacy Policy					
Power	.002(.001)*	n.s.	n.s.	.94(.01)***	.92***
Privacy	.02(.001)*	.01(.01)*	.03(.01)***	.88(.02)***	.89***
Safety	−.01(.004)**	−.05(.01)***	−.01(.01)*	.91(.01)***	.89***
Choice	n.s.	n.s.	n.s.	.92(.01)8**	.91***
Community	.004(.001)**	.03(.01)*	.01(.004)**	.93(.01)***	.95***
Engagement	.01(.004)*	n.s.	n.s.	.92(.01)***	.92***
Property	NA				
Improvement	n.s.	n.s.	n.s.	.94(.01)***	.95***
Care	NA				
Accountability	.005(.003)*	n.s.	.01(.01)*	.94(.01)***	.92***
Terms of Service					
Power	n.s.	n.s.	n.s.	.92(.01)***	.91***
Privacy	n.s.	n.s.	.01(.003)*	.92(.01)***	.93***
Safety	NA				
Choice	n.s.	−.05(.02)*	−.01(.004)*	.92(.01)***	.93***
Community	n.s.	n.s.	n.s.	.92(.01)***	.94***
Engagement	n.s.	n.s.	n.s.	.95(.01)***	.95***
Property	n.s.	n.s.	n.s.	.94(.01)***	.94***
Improvement	n.s.	n.s.	n.s.	.95(.01)***	.94***
Care	NA				
Accountability	n.s.	n.s.	n.s.	.92(.01)***	.91***

Note: Unstandardized regression coefficients are presented, with standard errors in parentheses.
NA indicates insufficient data points for temporal causality analysis, while n.s. denotes not statistically significant.
*** $p < .001$, ** $p < .01$, * $p < .05$.

In contrast, Table 6b outlines the significant negative Granger-caused influences between OpenAI's policies and the values in Twitter/X, TikTok, and Facebook. For Twitter/X, values such as improvement and choice were negatively influenced by OpenAI's policies. Improvement in Twitter/X's CG and PP exhibited a consistent negative relationship with OpenAI's CG and PP. Additionally, choice showed a significant negative association with OpenAI's PP and TOS, particularly in Twitter/X's TOS.

For TikTok, OpenAI's CG negatively influenced safety and power values within TikTok's CG, indicating a temporal reduction in these values following changes in OpenAI's policies. TikTok's TOS also showed a negative association with choice, driven by OpenAI's PP and TOS, suggesting potential divergences in how user choice was emphasized between the two platforms. For Facebook, negative influences were observed in the improvement and safety values. Both values experienced negative temporal associations with OpenAI's CG and PP, indicating potential conflicts or discrepancies between OpenAI's value structures and that of Facebook. The power value in Facebook's TOS also showed a negative association with OpenAI's PP.

Table 6. Summary of significant Granger-caused influences from OpenAI's policy changes on other platforms' values.

a. Summary of positive significant Granger-caused influence.

	OpenAI (Community Guidelines)	OpenAI (Privacy Policy)	OpenAI (Terms of Use)
Community Guidelines			
Twitter/X	Privacy Engagement		Privacy
TikTok	Privacy	Privacy	Choice Engagement Intellectual Property
Facebook	Community		
Privacy Policies			
Twitter/X	Privacy Choice Engagement Accountability	Community Accountability	
TikTok	Community Intellectual Property		Privacy
Facebook	Power Privacy Community Engagement Accountability	Privacy Community	Privacy Community Accountability
Terms of Service			
Twitter/X	Community Engagement Accountability	Privacy Engagement Intellectual Property Accountability	Privacy Engagement Intellectual Property Accountability
TikTok			Privacy
Facebook	Community Engagement		Accountability

b. Summary of negative significant Granger-caused influence

	OpenAI (Community Guidelines)	OpenAI (Privacy Policy)	OpenAI (Terms of Use)
Community Guidelines			
Twitter/X	Improvement	Improvement	Improvement
TikTok	Safety	Power	
Facebook		Improvement	Improvement
Privacy Policies			
Twitter/X	Power Improvement	Power Choice	Power Choice
TikTok	Power		
Facebook	Safety	Safety	Safety
Terms of Service			
Twitter/X	Safety Choice Improvement	Choice	Choice
TikTok		Choice	Choice
Facebook	Power	Safety	Safety

Self-lagged influence. All the significant Granger causality models displayed strong self-lagged influence, where the previous period's policies significantly predicted changes in the same policy type in the following period. This strong positive self-influence was consistently observed across the platforms, indicating a high degree of internal consistency and temporal continuity in policy changes.

Instantaneous causality influence. Instantaneous causality tests were conducted to examine whether OpenAI's policy changes had immediate, simultaneous effects on the policies of Twitter/X, TikTok, and Facebook. No significant instantaneous effects were found for any value or platform ($p > .10$ for all tests).

Contextualizing the assembling of GenAI and platform governance

Before discussing the implications of the value patterns, we contextualize how OpenAI and other social media platforms contributed to the contested process of assembling GenAI governance.

Since its inception in 2015, OpenAI has publicly emphasized its commitment to 'openness' (Hao, 2020; Widder et al., 2023) and its ambition to build 'safe' AI for the benefit of all. The discourse surrounding openness allows OpenAI to distinguish itself from other commercial AI labs like Google's DeepMind, though some have criticized it as a 'publicity stunt' (Hao, 2020) and self-serving rhetoric (Widder et al., 2023). In 2019, when OpenAI released GPT-2, it strategically mobilized the value of safety to market the tool and justify its closed governance by claiming it was 'too dangerous' due to potential misuse 'to generate deceptive, biased, or abusive language at scale' (OpenAI, as cited in Widder et al., 2023, p. 14). Indeed, the first step for assembling a policy is to translate certain issues into policy concerns and enroll other actors into the responsibility framework (Ureta, 2014). Safety became a problem that OpenAI and other social actors (e.g., users) should tackle. This rhetorical focus is reflected in OpenAI's early stage of intervention concerning GPT-3.0. As OpenAI (2022) stated, 'Our use case guidelines, content guidelines, and internal detection and response infrastructure were initially oriented towards risks that we anticipated based on internal and external research.'

In 2023, OpenAI merged its use case guidelines (renamed *Usage Guidelines* in November 2021) and content policies into a single document, *Usage Policies* (the CG analyzed previously). This policy is targeted at users developing applications or using OpenAI's services. It places a significant emphasis on safety. The February 2023 version stated: 'We want everyone to use our tools safely and responsibly … By following them, you'll ensure that our technology is used for good.' Then it listed the types of 'disallowed usage' of its model including 'illegal activity,' 'child sexual abuse,' 'political campaigning or lobbying,' 'activity that has high risk of physical harm,' and so on. OpenAI's policies have explicitly prohibited competitors from using its outputs for training AI models. Additionally, OpenAI emphasized user responsibility in preventing the 'misuse' of its tools that could cause harm or threaten others' privacy (January 2024 version). Despite the criticism of the biases in large language models (Bender et al., 2021), OpenAI highlighted its proactive efforts to make its models 'safer and more useful, by training them to refuse harmful instructions and reduce their tendency to produce harmful content.' Echoing the trend of platform governance, OpenAI's policies delineate the boundary of (legitimate) data extraction and legitimize self-governance through technical tools.

Nevertheless, OpenAI's earlier version (September 2022) did not specify how user data could be used to train AI models, only addressing this issue in April 2023, likely due to external pressure. In March 2023, ChatGPT experienced a data breach that exposed users' credit card information and other personally identifiable data (Thorbecke, 2023), leading to a ban in Italy and an FTC complaint in the U.S. In response, OpenAI (2023) published a blog post on April 5, explaining that its 'large language models are trained on a broad corpus of text that includes publicly available content, licensed content, and content generated by human reviewers.'[6] OpenAI added 'we want our models to learn about the world, not private individuals.' On April 27, it revamped its PP. The revised policy noted personal data could be used for training purposes and introduced an opt-out option for users. It allowed users to request corrections if they found ChatGPT's output produced 'factually incorrect personal information.' On the surface, these changes seemed to promote the values of power, privacy, and choice. However, OpenAI cautioned that users' requests might not be fulfilled due to the 'technical complexity' of their models. Besides the prescribed relationship between OpenAI and users, OpenAI's policies have prohibited competitors (e.g., ByteDance; Heath, 2023) from using its outputs for training AI models since 2022.

After cross-referencing the timeframe with policy changes and news coverage, there seems to be evidence suggesting that Facebook, Twitter/X, and TikTok have increasingly become part of the policy assemblage of GenAI governance since 2023. TikTok updated its PP in January to state users' information would be used 'to train and improve' its 'machine learning models and algorithms' and modified its CG in March to moderate AI-generated content due to concerns over misinformation. In June, Facebook updated its PP, allowing the company to use its users' posts and photos to train GenAI models. Similarly, Twitter/X revised its PP in August, stating that the company 'may use the information we collect and publicly available information' for training its AI models, despite Elon Musk having criticized Microsoft in April for 'illegally using Twitter data' for AI training (Leswing, 2023). This trend extends beyond the studied platforms. Google revised its policies in mid-July to allow itself to train AI models on users' data. On 13 February 2024, FTC published a blog post, warning against the deceptive practice of 'obtaining artificial consent' to use consumer data for training AI products (Staff in the Office of Technology and The Division of Privacy and Identity Protection, 2024).

This trend was likely driven not only by the growing prominence of GenAI but, more importantly, the scarcity and decline of 'high-quality' training data sources. Longpre et al. (2024) found that many websites increasingly incorporated restrictions on AI-related web crawlers in their robots.txt files and terms of service between 2023 and 2024. This may explain why the studied platforms have increasingly broadened the scope of user and copyrighted data usage in their policies (Metz et al., 2024). Like OpenAI, tech companies modified their policies to safeguard their user data and content from being exploited by rival AI models. As such, a wide array of actors, ranging from tech companies and policymakers to users, were enrolled into the GenAI governance assemblage. However, these platform policy updates seemed to primarily prioritize tech companies' strategic interests, while positioning users as mere data sources and sidelining their voices within GenAI governance. While these rhetorical constructions may represent the continuation of tech companies' data practices and discursive strategies, they produce new territories by redefining who legitimately holds the right to extract and use user data to train their AI models.

Since we primarily examined publicly available policies, it would be difficult to fully capture the underlying dynamics. Yet, these incidents show OpenAI's governance framework was assembled through the interplay between OpenAI and other social actors. Moreover, the GenAI policy assemblage was co-evolved with contingent events across interdependent microsystems.

Discussions

Through a comparative analysis of policy documents of OpenAI, Twitter/X, TikTok, and Facebook, this article explores the assembling and co-evolution of platform governance in the face of GenAI. At the lexical level, OpenAI's policy documents became longer and less complex, whereas its readability fluctuated between 2022 and 2024. We observed changes in the lexical characteristics of Twitter/X, TikTok, and Facebook's policies following the introduction of OpenAI's policies. This is consistent with previous research which suggests that platform policies are likely to develop a more nuanced and complex structure in response to external events (Dubois & Reepschlager, 2024). However, it is noteworthy that the analysis focused on general patterns of change rather than AI-specific changes. The emergence of GenAI, like any new technology, is unlikely to transform everything in a short period of time. For example, TikTok updated its policies in December 2023 to require users to waive the rights to pursue any legal actions against the company, likely in response to ongoing lawsuits concerning child safety and privacy, rather than GenAI. As illustrated below, echoing Van Dijck's (2013) observations, we argue that distinct platform microsystems are sensitive to OpenAI's policy changes.

At the discursive level, we traced the evolution of key platform values such as privacy, engagement, accountability, and safety, as these values were articulated in OpenAI's CG, PP, and TOS. Our findings underscore the dynamic nature of platform governance, highlighting areas of convergence and divergence between OpenAI and other platforms. It revealed three prominent value patterns in the relationship between the policies of OpenAI and the three platforms: (1) positively-aligned values, (2) divergent values, and (3) floating values. First, positively-aligned values include privacy, engagement, and accountability. For instance, OpenAI's PP had a significant positive influence on the value of privacy in both Twitter/X and Facebook's policies. The consistent positive relationship suggests a convergence in how these platforms prioritize and handle privacy-related issues, likely reflecting the industry-wide importance of data protection and user privacy in response to evolving regulations and public demand. Engagement also followed a positive trajectory, especially in Twitter/X and Facebook, where changes in OpenAI's CG were closely followed by increases in engagement in these platforms' policies. As OpenAI placed more emphasis on facilitating user interaction and participation, other platforms similarly adjusted their policies to enhance user engagement. Accountability emerged as another positively-aligned value, particularly in Facebook's policies, where OpenAI's CG and TOS positively influenced the accountability value. The alignment of accountability-focused policies suggests a shared direction in promoting mechanisms for platforms and users to take responsibility for their content and interactions. As such, these companies strategically mobilized the rhetoric associated with these value-laden terms to legitimize their self-governance.

Divergent values like improvement, choice, and power exhibited negative associations with OpenAI's policies, particularly in Twitter/X and TikTok. For instance, OpenAI's PP negatively influenced choice in TikTok's TOS and Twitter/X's PP, indicating a shift away from user autonomy on these platforms. Similarly, improvement consistently showed negative associations, especially in Twitter/X's policies, implying that other platforms deprioritized innovation as OpenAI advanced its platform. Power, particularly in Facebook's TOS and TikTok's CG, demonstrated a negative association with OpenAI's policy changes. While OpenAI might have increased emphasis on platform or user governance (e.g., content moderation or protection of intellectual property), other platforms might have reduced their focus on these aspects, indicating a divergence in governance and enforcement strategies.

Finally, floating values, including safety, community, and intellectual property protection, demonstrated both positive and negative associations depending on the platform and policy type. For instance, OpenAI's PP negatively influenced safety in Facebook's TOSand TikTok's CG, while no significant associations were found in Twitter/X's policies. This fluctuation could suggest that the emphasis on user and platform safety shifted across platforms and time, with OpenAI's focus on safety prompting other platforms to either deprioritize or adjust their safety-related policies in different directions. The influences of OpenAI's prescribed values of community and intellectual property protection, similarly, was not uniformly adopted across all platforms. There are two possible explanations. First, GenAI remains an emerging technology, meaning its values and governance approaches have yet to stabilize. Consequently, platforms are in the process of adapting their values to the evolving data-driven ecosystem. Second, these findings may reflect the patchwork nature of platform governance, where companies adopt and modify governance frameworks based on industry standards while maintaining flexibility to tailor policies to their specific microsystems.

The observed interdependence of OpenAI's and social media platforms' policy documents, together with the contextualization of such changes, showcase the contested process through which these companies attempted to problematize GenAI's safety concerns, selectively assign responsibility to users, and (re)stabilize their 'legitimate' role in extracting user data for AI training. While existing research often focused on how distinct platforms articulated their own governance frameworks independently, this study contributes to understanding the relational nature of platform governance. The tech industry is not just economically concentrated; instead, such concentration may also be reflected in the convergence and co-evolution of their governance. Practically, for policymakers, our findings suggest that regulatory frameworks should account for the cascading effects of policy changes across platforms. The alignment in privacy-related values, for instance, underscores the importance of coordinated regulation that addresses data protection and privacy issues holistically. Meanwhile, the divergence in values like choice points to the need for regulations that ensure platforms maintain transparency and user control in how they govern data and content.

At the time of writing, the GenAI boom continues – tech companies, investors, and state actors rushing to capitalize on this trend frequently emphasize the capabilities of advanced AI models and the strategic importance of crafting policies that facilitate what they frame as the inevitable development of AI. While companies such as OpenAI have established licensing agreements with some news publishers, AI-related copyright lawsuits remain ongoing. Strategic alliances, meanwhile, are often temporary, reflecting shifting interests within the rapidly evolving GenAI landscape. For example, Microsoft announced that it would no longer become OpenAI's exclusive cloud provider in January 2025. These incidents reveal the multifaceted and situated nature of GenAI development and governance. Instead of essentializing these dynamics as following an inevitable, singular trajectory, assemblage thinking provides a sensitizing tool to theorize how 'assemblages establish territories as they emerge and hold together but also constantly mutate, transform and break up' (Müller, 2015, p. 29). Analyzing the interdependencies of GenAI and platform governance frameworks can also help understand the discursive work that stabilizes and repairs particular AI-related data practices and territories.

Limitations and future research

While this study provides valuable insights into the co-evolution of platform governance in the age of GenAI, it is not without limitations. First, the study focuses on a limited number of platforms. Future research should expand the scope to include more platforms and different types of policy documents. Second, while our use of VAR models and Granger causality tests provides robust empirical evidence of temporal influence, our findings primarily capture direct policy interdependencies rather than broader external forces that may simultaneously shape governance decisions across platforms. Although our analyses confirm that social media platforms do not appear to exert a significant lagged or instantaneous influence on OpenAI's governance frameworks, this does not preclude the possibility that regulatory interventions, industry-wide AI developments, or public discourse could be common drivers of policy changes across multiple platforms. Additionally, examining the role of regulatory agencies, civil society organizations, and transnational governance bodies in shaping platform policies would provide a more comprehensive understanding of the evolving governance landscape. Future research should explore how these actors become (dis)assembled into GenAI governance. This also calls attention to power-relations 'in terms of how some elements of assemblages are negated and others are more durable' (Gerrard & Thornham, 2020, p. 1268; see also Latour, 2005). Finally, while this study analyzes textual policy changes, future research could investigate how governance shifts translate into actual enforcement practices and user experiences. A mixed-methods approach integrating computational text analysis with ethnographic or experimental methods could examine the effectiveness and implications of platform governance adaptations.

Overall, this study highlights the complex and interdependent nature of platform governance in the context of GenAI. Through assemblage thinking, we examined how OpenAI's policies influenced the governance frameworks of Twitter/X, TikTok, and Facebook, revealing both convergence and divergence in key platform values. These findings offer important theoretical and practical insights into how platform governance is assembled and reshaped in response to emerging technologies, regulatory pressures, and public concerns. As the ecosystem of GenAI continues to evolve, understanding the interplay between platforms and their governance structures will be crucial for navigating the future of platform governance.

Notes

1. For OpenAI, we examined its Usage Policies, but for the sake of consistency, we used CG to refer to it in the analysis.
2. For OpenAI, we examined its Terms of Use, but for the sake of consistency, we used TOS to refer to it in the analysis.
3. In a few instances, we identified discrepancies between the policy change logs published by the platforms and the policy versions we scraped from the Wayback Machine. For example, one version of OpenAI's policy, which was reported to have undergone significant revisions, only appeared in the Wayback Machine data several days after the claimed revision date. This discrepancy could be due to two potential reasons: (1) the platform's revision logs may not have immediately reflected changes on the official public policy pages, with the updates becoming effective a few days later, or (2) the Wayback Machine may have experienced a technical delay in capturing the most up-to-date snapshot of the policy page. To

maintain consistency in our statistical and referential analyses, we used the scraped policy data from the Wayback Machine across all platforms. We carefully examined the potential influence of these rare discrepancies and confirmed that they did not cause any temporal mismatch or inaccuracies in the time-series analysis.

4. We initially extracted 387,461 sections from 8,516 archived policy documents spanning all four platforms. After removing duplicates at both the document and section levels, we retained 3,741 unique sections for analysis.
5. To assess the robustness of our findings, we conducted additional analyses testing the alternative hypothesis that social media platforms' policy changes predict subsequent changes in OpenAI's policies. The results indicate that the majority of these relationships are not statistically significant, nor do they exhibit any consistent patterns across policy domains.
6. In January 2024, OpenAI argued that 'it would be impossible to train today's leading AI models without using copyrighted materials' (Milmo, 2024).

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