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10 **UNITED STATES DISTRICT COURT**
11 **NORTHERN DISTRICT OF CALIFORNIA**
12 **SAN JOSE DIVISION**

13 TIKTOK, INC.,

14 Plaintiff,

15 v.

16 ROB BONTA, ATTORNEY GENERAL OF
17 THE STATE OF CALIFORNIA, in his official
18 capacity,

19 Defendant.

Case No. 5:25-cv-09789-EJD

**BRIEF OF ELECTRONIC PRIVACY
INFORMATION CENTER AND LAW &
TECHNOLOGY SCHOLARS AS *AMICI
CURIAE* IN SUPPORT OF
DEFENDANT**

Hearing Date: May 7, 2026

Time: 9:00 a.m.

Judge: Hon. Edward J. Davila

Court: Courtroom 4, 5th Floor

20 META PLATFORMS, INC.,

21 Plaintiff,

22 v.

23 ROB BONTA, ATTORNEY GENERAL OF
24 THE STATE OF CALIFORNIA, in his official
25 capacity,

26 Defendant.

Case No. 5:25-cv-09792-EJD

**BRIEF OF ELECTRONIC PRIVACY
INFORMATION CENTER AND LAW &
TECHNOLOGY SCHOLARS AS *AMICI
CURIAE* IN SUPPORT OF
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Hearing Date: May 7, 2026

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GOOGLE LLC and YOUTUBE, LLC,

Plaintiff,

v.

ROB BONTA, ATTORNEY GENERAL OF
THE STATE OF CALIFORNIA, in his official
capacity,

Defendant.

Case No. 5:25-cv-09795-EJD

**BRIEF OF ELECTRONIC PRIVACY
INFORMATION CENTER AND LAW &
TECHNOLOGY SCHOLARS AS *AMICI
CURIAE* IN SUPPORT OF
DEFENDANT**

Hearing Date: May 7, 2026
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1 **INTEREST OF THE *AMICI CURIAE***

2 The Electronic Privacy Information Center (“EPIC”) is a public interest research center
3 in Washington, D.C., established in 1994 to focus public attention on emerging privacy and
4 civil liberties issues.¹ EPIC regularly participates as amicus in cases concerning the First
5 Amendment implications of platform regulation. *See* EPIC, *The First Amendment* (2026).²

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24 ¹ *Amici* certifies that no person or entity, other than *Amici*’s own staff or counsel, made a
25 monetary contribution to the preparation or submission of this brief or authored this brief, in
26 whole or in part.

27 ² [https://epic.org/issues/platform-accountability-governance/the-first-amendment-and-platform-](https://epic.org/issues/platform-accountability-governance/the-first-amendment-and-platform-regulation/)
28 [regulation/](https://epic.org/issues/platform-accountability-governance/the-first-amendment-and-platform-regulation/).

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22 INTRODUCTION

23 Under *Moody v. NetChoice*, 603 U.S. 707 (2024), some of the decisions a company
24 makes to generate an algorithmic feed may be expressive choices protected by the First
25 Amendment. SB 976’s limits on the categories of personal data a company can use to generate
26 an algorithmic feed do not burden those expressive choices. Companies do not use the regulated
27 categories of data to make expressive choices, and limiting the use of this data does not impact
28 feed generation choices that are expressive.

1 SB 976 targets a particularly harmful and invasive aspect of feed generation in which a
2 company builds and compares behavioral profiles of users to predict the content that is most
3 likely to lead to user behavior that will maximize ad revenue. This Court, the Ninth Circuit, and
4 the Supreme Court have all questioned whether use of these kinds of “algorithms [that] respond
5 solely to how users act online—giving them the content they appear to want, without any regard
6 to independent content standards,” is expressive. *Moody*, 603 U.S. at 736 n.5. And for good
7 reason.

8 Behavioral profiling for feed generation is very different than the content moderation
9 practices the *Moody* Court recognized may be expressive. Content moderation involves
10 companies removing and downranking content that violates their policies. These curatorial
11 decisions are closely analogous to those long recognized as protected editorial judgement. Laws
12 that override content moderation decisions may compel companies to publish messages and
13 viewpoints they deem unfit to publish.

14 SB 976 does not force companies to publish messages they do not think are fit for
15 publication, nor does it prevent them from publishing messages they wish to publish. The use of
16 behavioral profiling for feed generation is unlike any exercise of editorial discretion recognized
17 in precedent. Behavioral profiling algorithms do not select and arrange content based on a
18 company’s judgment that the message is fit for publication. The curatorial choices do not
19 depend on an evaluation of the content’s message, nor do they reflect any human intent to
20 communicate a coherent message, idea, or theme. They are designed to evaluate *users*, not
21 messages, and so are blind to the meaning of the media selected and how that meaning impacts
22 the message sent by the overall compilation. In fact, these algorithms often amplify messages
23 that the companies claim they do not wish to publish at all. That is in large part because humans
24 give the machines a non-expressive goal—maximize usage of the platform—and the machine
25 decides the rules for selecting and ranking content to accomplish that goal. The machines are
26 not directed to understand—or care—what messages they are selecting and amplifying.

27 Courts have long recognized in a variety of contexts that conduct can have both
28 expressive and non-expressive components. Feed generation involves both expressive and non-

1 expressive activities, and behavioral profiling more resembles the kinds of functional, non-
2 expressive activities that courts have recognized occur alongside expression. Because
3 behavioral profiling is not inextricably intertwined with content moderation, the state can
4 regulate it without impacting companies’ expression.

5 ARGUMENT

6 I. Content moderation decisions can be expressive.

7 In *Moody*, the Supreme Court signaled that a law compelling a social media company to
8 publish what it would rather exclude restricts the company’s exercise of editorial discretion. *See*
9 *Moody*, 603 U.S. at 728. The process by which companies exclude or otherwise express
10 disapproval of unwanted content is called content moderation. *Id.* at 719. Content moderation is
11 similar to traditional editorial discretion because both involve a speech compiler deciding
12 whether to include or exclude pieces of media based on how each piece would affect the overall
13 message of the compilation. *Id.* at 731–32.

14 Content moderation begins with the employees of a social media company establishing
15 content guidelines for the platform. These guidelines “list the subjects or messages the platform
16 prohibits or discourages—say, pornography, hate speech, or misinformation on select topics.”
17 *Moody*, 603 U.S. at 719. Content guidelines are heavily laden with humans’ value judgments
18 about the semantic content of the media, prohibiting media judged to be distasteful, low-quality,
19 or irrelevant. *See, e.g., Community Standards, Meta (2026)*.⁴ While content moderation may not
20 be perfect, it reflects companies’ conscious efforts to avoid publishing content they do not think
21 is fit for publication.

22 The *Moody* Court signaled in dicta that content moderation can be protected editorial
23 discretion. “When the platforms *use their Standards and Guidelines to decide* which third-party
24 content those feeds will display, or how the display will be ordered and organized, they are
25 making expressive choices.” *Moody*, 603 U.S. at 740 (emphasis added). In the Court’s view, a
26 social media company, through content moderation systems, decides “whether—and, if so,

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⁴ <https://transparency.meta.com/policies/community-standards/>.

1 how—to convey posts having a certain content or viewpoint,” and “[t]hose choices rest on a set
2 of beliefs about which messages are appropriate and which are not.” *Id.* at 738. A company that
3 does not want to spread pro-Nazi beliefs, say, acts expressively when excluding pro-Nazi
4 media. A law that “direct[s] a company to accommodate messages it would prefer to exclude”
5 thus infringes on the company’s protected editorial discretion. *Id.* at 731.

6 The *Moody* Court saw their decision as a direct application of decades of Supreme Court
7 precedent recognizing the rights of speech compilers to exclude messages and viewpoints they
8 do not wish to carry. *See id.* at 728–33 (discussing the Court’s editorial discretion precedent).
9 The editorial discretion cases are themselves part of the Court’s compelled speech precedent
10 that prohibits the government from “coopt[ing] an individual’s voice for its own purposes.” 303
11 *Creative LLC v. Elenis*, 600 U.S. 570, 592 (2023). They involve the government overriding a
12 person’s or group’s choice not to speak on a given topic or to not express a specific viewpoint
13 or message. To the extent that companies’ content moderation decisions reflect the editorial
14 judgements of their leaders and employees, they fit squarely within this precedent.

15 **II. The use of surveillance data to generate addictive feeds is not expressive.**

16 SB 976 regulates social media companies’ use of personal data to select and rank
17 content in users’ feeds. Cal. Health & Safety Code § 27000.5(a).⁵ While limits on the use of
18 personal data may trigger First Amendment scrutiny if they “are based on the content of speech
19 and are aimed at a particular viewpoint,” *Sorrell v. IMS Health, Inc.*, 564 U.S. 552, 565
20 (2011), there is no general rule that data use regulations automatically implicate or run afoul of
21 the First Amendment. What’s more, social media companies do not generally use the regulated
22 categories of personal data to engage in expressive content moderation but to fuel revenue-
23 maximizing components of their recommendation systems that extend usage of their products.
24 Unlike content moderation algorithms, which evaluate the message or viewpoint of content to
25 determine whether it violates a company’s policies, revenue-maximizing algorithms evaluate
26 *users* by measuring how likely it is the user will interact with a given piece of media, regardless

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28 ⁵ All statutory citations are to the California Health and Safety Code unless otherwise noted.

1 of its message or viewpoint. *See* Neil Richards & Woodrow Hartzog, *Against Engagement*, 104
2 Boston U. L. Rev. 1151, 1154 (2024). This behavioral profiling lacks every characteristic of
3 protected editorial judgement. It is functional, not expressive. It matters little that companies
4 combine non-expressive behavioral profiling with expressive content moderation to generate a
5 single algorithmic feed. Courts have long recognized that conduct can have both expressive and
6 non-expressive elements. When the State regulates a non-expressive element, the First
7 Amendment is implicated, at most, only incidentally. Since behavioral profiling and content
8 moderation are entirely separate processes, regulating the former has no incidental impact on
9 the latter.

10 **A. Behavioral profiling in recommendation systems generates content choices**
11 **based on users’ behavior, not the message or viewpoint of content.**

12 Companies use multiple types of algorithms to generate algorithmic feeds. As discussed
13 in Part I, some of these algorithms implement a company’s views on the value of certain
14 messages, topics, or viewpoints. Companies do not use individuals’ personal data for this
15 purpose but for another: the revenue-maximizing aspects of their recommendation systems.
16 These algorithms evaluate user behavior to maximize the probability that a specific user will
17 engage in behavior that increases the company’s ad revenue. *See* Ravi Iyer, *Feed Algorithms*
18 *Contain both Expressive and Functional Components*, USC Neely Center for Ethics and
19 Technology (Dec. 10, 2024);⁶ Egelman Decl. ¶¶ 17–18. For many companies, the behavior they
20 are trying to maximize is “engagement,” or the probability that the user will interact with a
21 specific piece of content. *See* Arvind Narayanan, *Understanding Social Media Recommendation*
22 *Algorithms*, The Knight First Amendment Institute at Columbia University 20 (2023);⁷ Egelman
23 Decl. ¶¶ 16–19.

24 The primary fuel for revenue-maximizing algorithms is user behavioral data collected
25 through surveillance, not explicit user feedback or the topic, meaning, or viewpoint of content.

26 _____
27 ⁶ [https://neely.usc.edu/2024/12/10/algorithms-contain-both-expressive-and-functional-
components/](https://neely.usc.edu/2024/12/10/algorithms-contain-both-expressive-and-functional-components/).

28 ⁷ [https://s3.amazonaws.com/kfai-documents/documents/4a9279c458/Narayanan---
Understanding-Social-Media-Recommendation-Algorithms_1-7.pdf](https://s3.amazonaws.com/kfai-documents/documents/4a9279c458/Narayanan---Understanding-Social-Media-Recommendation-Algorithms_1-7.pdf).

1 See Narayanan, *supra*, at 18. The behavioral data used by these algorithms can include likes,
2 clicks, comments, time spent watching, time spent lingering, and other indications that a piece
3 of content held a user’s attention. *Id.* at 18–19; *e.g.*, Zhou Decl. ¶ 12; Goodrow Decl. ¶ 20;
4 Backstrom Decl. ¶ 7.

5 To create the revenue-maximizing algorithm, social media companies use machine
6 learning techniques to direct a computer to determine what combination of the surveillance data
7 best predicts the behavior they are trying to maximize—*e.g.*, engagement. See Richards &
8 Hartzog, *supra*, at 1162–63; Backstrom Decl. ¶ 7 (“Meta’s prediction models include the
9 likelihood that the user will meaningfully interact with a post, the likelihood that the user’s
10 interactions with a post will encourage others to share more content in the future that is valuable
11 to the user, how likely the user is to find the post worth their time, and how likely the user is to
12 click on the profile of a post’s author.”); Zhou Decl. ¶ 15; Goodrow Decl. ¶ 11 (explaining that
13 YouTube’s Recommender System “is not static”, “is based on billions of signals”, and “varies
14 depending on how to accomplish the primary goal of the YouTube Recommender System,”
15 which is to make a prediction about a user.) It is thus the computer, and not humans, that
16 analyzes users’ personal data and determines the specific rules for how the data will influence
17 the content shown to a given user and in what order. The algorithm then constructs profiles of
18 users from the surveillance data, uses these profiles to compare each user to other users, and
19 shows users media that users with similar profiles engaged with heavily. See Narayanan, *supra*,
20 at 22; Zhou Decl. ¶ 11; Goodrow Decl. ¶ 15 (The YouTube Recommender System “considers
21 billions of signals, including for example what other similarly situated users also enjoyed” and
22 “if the signals support it, the YouTube Recommender System could find other videos on similar
23 subject matters (such as self-driving cars) viewed and enjoyed by other users with similar
24 interests and surface those videos to that user . . .”).

25 In contrast to content moderation, which evaluates the message expressed by media and
26 whether to publish that message, revenue-maximizing behavioral profiling algorithms do not
27 evaluate the viewpoint, topic, or quality of media. The algorithms, according to at least one
28 major social media company, are “content-neutral.” TikTok Compl. ¶ 160. Companies use them

1 not to shape a coherent message out of the media selected but to accomplish the functional task
2 of inducing profitable user behavior. *See Iyer, supra; see generally* Brett Frischmann & Evan
3 Selinger, *Re-Engineering Humanity* (2018). Any message goes—including content that violates
4 the company’s own policies—so long as it maximizes profitable user behavior. Indeed, separate
5 content moderation algorithms are necessary to remove violative content precisely because the
6 revenue-maximizing algorithms are not designed to select or rank content based on the message
7 expressed.

8 The behavioral profiling technology companies use to generate revenue-maximizing
9 algorithmic feeds is unlike any curation method used by traditional publishers. Brett M.
10 Frischmann & Peter Ormerod, *Regulating Manipulative Design Is Not Preempted by Section*
11 *230 or the First Amendment*, 75 Emory L.J. ___ (forthcoming May 2026) (manuscript at 31–33).⁸
12 Newspapers, magazines, television networks, and film studios may consider aggregate audience
13 data to determine what topics, ideas, and viewpoints their audiences are interested in, but they
14 do not surveil individuals’ reading or viewing habits and generate personalized publications for
15 each person based on this behavior. What Plaintiffs are doing with user data is like a cable
16 operator using subscribers’ viewing habits to choose the programming that appears on their
17 televisions without knowing or caring what programs they are picking—to, essentially, change
18 the channel on subscribers in a pattern most likely to maximize their revenues. Notably, SB 976
19 does not prohibit companies from using aggregate user data to generate algorithmic feeds, and
20 so regulated entities are still able to be responsive to audience preferences in the same ways
21 traditional publishers are.

22 It is also worth noting that behavioral profiling is not synonymous with personalization.
23 *See generally* Knight Georgetown Institute, *Better Feeds: Algorithms That Put People First*
24 (2025).⁹ Indeed, Plaintiffs’ characterization of their recommendation systems as tools reflecting
25 user preferences is disingenuous, as such feeds do not reflect—and often override—the actual

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27 ⁸ Available at <https://ssrn.com/abstract=5587430>.

28 ⁹ https://kgi.georgetown.edu/wp-content/uploads/2025/02/Better-Feeds_-_Algorithms-That-Put-People-First.pdf.

1 preferences of users. *See, e.g.*, Compl. ¶ 265–72, *Massachusetts v. TikTok Inc. et al.*, No. 2484-
2 cv-2638-BLS-1 (Mass. Sup. Ct. Feb. 3, 2025) (explaining how TikTok introduced a “Refresh”
3 tool for users to reset their engagement data if they were unhappy with their feed, then decided
4 to degrade the tool’s effectiveness when users’ fondness for it caused their engagement numbers
5 to drop); Arturo Béjar, et al., *Teen Accounts, Broken Promises: How Instagram Is Failing To*
6 *Protect Minors* 34 (Sep. 2025) (finding that Meta’s “not interested” feature “did not
7 significantly alter the type of content recommended by Instagram”). Some of the Plaintiffs also
8 claim that they personalize users’ experiences by avoiding publishing certain messages to
9 certain people, like inappropriate content to minors, but some of Plaintiffs’ age-appropriate
10 features have been found to not work as claimed. *See, e.g., id.* at 33–40 (finding that
11 Instagram’s filters for sensitive content do not operate as promised.)

12 There are many other ways companies might provide personalized feeds, like giving
13 users effective tools to specify for themselves what content they would like to appear in their
14 feed. SB 976 leaves companies with ample room to provide such personalization. YouTube, for
15 instance, can still provide minors with feeds containing content from channels they subscribe to.
16 YouTube can also curate its own channels for various interests, like college basketball, crochet,
17 or cats, and allow users to add these channels to their personalized feeds. YouTube can further
18 refrain from publishing certain messages to certain people, as SB 976 only restricts the use of
19 personal data to *select* media, not to *remove* it. § 27000.5(a). And YouTube could rank the
20 content in personalized feeds in any number of ways, including quality, popularity, timeliness,
21 or any other non-user-specific metric. Such personalization would be *more* likely to give users
22 what they want, not less, and better respect their privacy and autonomy.

23 **B. Using revenue-maximizing behavioral profiling algorithms is not an exercise**
24 **of protected editorial discretion.**

25 The *Moody* Court recognized that behavioral profiling is distinct from content
26 moderation and that this distinction is constitutionally salient. While laws overriding
27 companies’ content moderation decisions fall squarely within the Court’s prior precedent on
28 editorial discretion and compelled speech, the same is not true of laws that regulate the use of

1 algorithms that “respond solely to how users act online.” *Moody*, 603 U.S. at 736 n.5. As Justice
2 Barrett wrote in her concurrence, “The First Amendment implications . . . might be different”
3 for “a platform’s algorithm [that] just presents automatically to each user whatever the
4 algorithm thinks the user will like—e.g., content similar to posts with which the user previously
5 engaged.” *Id.* at 746 (Barrett, J., concurring). The Ninth Circuit agreed that these feed
6 generation decisions are “probably not expressive.” *NetChoice, LLC v. Bonta*, 152 F.4th 1002,
7 1014 (9th Cir. 2025) (*NetChoice II*).

8 Indeed, the use of behavioral profiling to make revenue-maximizing decisions lacks
9 every characteristic of protected editorial discretion. Behavioral profiling does not involve the
10 company choosing to include or exclude content based on the message, idea, or theme
11 communicated. It also does not reflect any intent to communicate a message. As a result, the
12 company does not actually communicate any coherent message, idea, or theme to users through
13 the behavioral profiling process.

14 Expressive editorial decisions involve evaluating the communicative content of third-
15 party speech and choosing to include or exclude based on the message expressed. *See* Tim Wu,
16 *Machine Speech*, 161 U. Pa. L. Rev. 1495, 1521, 1528 (2013) (noting “knowing selection” as a
17 signature of expression). Most of the tentpole editorial discretion cases concern the
18 government’s interference with a speech compiler’s choice to exclude third-party speech based
19 on the message communicated by the third-party speech. The parade organizers in *Hurley v.*
20 *Irish-Am. Gay, Lesbian & Bisexual Grp. of Bos.*, 515 U.S. 557 (1995), wanted to exclude a float
21 because they thought its pro-LGBTQ message was inappropriate for an event celebrating Irish-
22 American heritage. *Id.* at 562. The Miami Herald in *Miami Herald Pub. Co. v. Tornillo*, 418
23 U.S. 241 (1974), refused to publish a response from a political candidate whose viewpoint the
24 paper did not think merited publishing. *Id.* at 256. The power utility in *Pac. Gas & Elec. Co. v.*
25 *Pub. Utilities Comm’n of California*, 475 U.S. 1 (1986), did not want to include messages from
26 a citizens rights group in its customer mailings that would likely critique or contradict the views
27 of the company. *Id.* at 12–13. And *Moody* concerned social media companies’ decisions not to
28 “convey posts having a certain content or viewpoint.” *Moody*, 603 U.S. at 738.

1 The expressiveness of a choice to include third-party speech in a compilation also
2 depends on whether the decision relates to what the third-party speech communicates, either
3 individually or collectively, and whether the compiler’s choices reflect their *own* message. For
4 instance, in *Turner Broad. Sys., Inc. v. F.C.C.*, 512 U.S. 622 (1994), cable operators were
5 recognized to be engaged in expression when they chose channels to include in their cable
6 packages because they “[sought] to communicate messages on a wide variety of topics and in a
7 wide variety of formats.” *Id.* at 636 (quoting *Los Angeles v. Preferred Communications, Inc.*,
8 476 U.S. 488, 494 (1986)). In other words, cable operators were engaged in expression not
9 because they chose whatever cable channels viewers wanted to see, but because each individual
10 channel was chosen, *based on its topic*, to contribute variety to the overall package. By limiting
11 the number of channels that cable operators were able to pick themselves, the government
12 limited the specific messages, topics, and formats the cable operators could choose to include,
13 and consequently constrained the intentionally curated variety of their offerings. *Id.* at 637.
14 Similarly, marches and parades are the expression of the organizers when they make a
15 “collective point” that reflects the organizers’ view or theme—for instance, celebration of Irish-
16 American heritage. *Hurley*, 515 U.S. at 568. When parade organizers select marchers to include,
17 they choose them based on the message they express so that the collective point is readily
18 apparent to those watching. The *Moody* Court noted that *Tornillo* and its progeny are
19 distinguishable from *PruneYard Shopping Center v. Robins*, 447 U.S. 74 (1980), and *Rumsfeld*
20 *v. Forum for Academic and Institutional Rights, Inc.*, 547 U.S. 47 (2006), because, in the latter
21 two cases, the government’s action “did *not* affect the complaining party’s own expression.”
22 *Moody*, 603 U.S. at 730.

23 Companies’ revenue-maximizing behavioral profiling algorithms do not evaluate the
24 message, topic, viewpoint, or speaker of content when deciding whether to include it in a user’s
25 feed and, consequently, do not use this information to determine what content to select. In a
26 TikTok employee’s own words, the algorithm “doesn’t care about the content—it doesn’t have
27 an agenda. It doesn’t qualitatively understand” the content it selects and ranks for users. TikTok
28 Compl. ¶ 160; *see also* Knight Georgetown Institute, *supra*, at 12–13 describing non-content

1 signals to which engagement-maximizing algorithms respond). That is because companies are
2 not *trying* to communicate anything through the individual or collective decisions of their
3 revenue-maximizing algorithms. Companies deploy behavioral profiling with the sole aim of
4 engineering a specific behavioral response in users—with no regard for the message that
5 including or excluding the content sends to the user. *See* Frischmann & Selinger, *supra*.

6 Because companies design their behavioral profiling algorithms to “solely respond to
7 prior user activity, there is no apparent message [of the company] being conveyed” by those
8 algorithms’ decisions. *NetChoice, LLC v. Bonta*, 761 F. Supp. 3d 1202, 1221 (N.D. Cal. 2024)
9 (*NetChoice I*). Consider a feed dictated by such decisions. When a company’s algorithm selects
10 third-party speech for inclusion in the feed, the “overall message is distilled from the individual
11 presentations along the way, and each unit’s expression is perceived by spectators as part of the
12 whole.” *Hurley*, 515 U.S. at 577. A feed’s overall message should thus derive from the
13 messages of the individual posts the algorithm selects, which “in the aggregate [] give the feed a
14 particular expressive quality.” *Moody*, 603 U.S. at 738. But because behavioral profiling
15 algorithms choose content for inclusion based purely on the probability that it will induce a user
16 into staying on the platform, not on the message expressed by the content, the resulting
17 compilations are often a hodge-podge of messages that lack a “common theme.” *Hurley*, 515
18 U.S. at 576. The output is equivalent to a group of people walking together carrying a random
19 assortment of signs with no collective purpose and no coherent message, theme, or viewpoint.
20 Each participant in this walk may be engaged in expression through their individual signs and
21 chants, but the *organizers* failed to craft any message through their decision making and
22 selection process. And just as a parade or a protest without a message is “just motion,” *id.* at
23 569, feed personalization through behavioral profiling is just an endless scroll.

24 The only potential message Plaintiffs claims their use of behavioral profiling algorithms
25 might send is something along the lines of, “You may find this content interesting.” Google
26 Mot. for Prelim. Inj. 12; (describing YouTube’s message as “You are likely to find interesting
27 the compilation of videos we have selected for you.”); Meta Mot. for Prelim. Inj. 6 (describing
28 Meta’s intended message to be that users’ “particular interests and preferences are reflected on”

1 Meta’s platforms); TikTok Mot. for Prelim. Inj. 15 (describing its “For You” feed’s message as
2 “TikTok thinks the displayed content will be interesting, informative, or entertaining to the
3 individual”). These are not the “creator’s message.” *NetChoice I*, 761 F.Supp.3d at 1222. They
4 are not the same as the Plaintiffs *themselves* saying “we think this content is interesting.” These
5 are just ways of saying “we personalized this feed for you,” which in turn is just a description of
6 the conduct that the Plaintiffs say they are engaged in. What’s more, Plaintiffs’ purported
7 message is not “distilled from the individual presentations along the way.” *Hurley*, 515 U.S. at
8 577. Indeed, it is unlikely that a user would understand this message just by looking at the
9 content selected for the feed. To the extent users understand that their feeds are personalized, it
10 is likely because companies typically communicate that their algorithmic feeds are personalized
11 in other ways, e.g., by labeling the feeds as such, providing user interface controls that indicate
12 personalization, or through branding. *See, e.g.*, TikTok Mot. for Prelim. Inj. 5 (explaining that
13 TikTok’s primary personalized feed is labeled “For You”).

14 The generic personalization messages Plaintiffs claim to communicate could also be
15 attributed to pretty much all personalized conduct, which would lead to all personalization
16 “becom[ing] expressive and receiv[ing] speech protections” even though “the Supreme Court
17 has made clear that there is not [a] ‘limitless variety of conduct that can be labeled “speech”
18 [even when] the person engaging in the conduct intends thereby to express an idea.’ ”
19 *NetChoice I*, 761 F. Supp. 3d at 1222 (quoting *United States v. O’Brien*, 391 U.S. 367, 376
20 (1968)). Many products and services use consumers’ personal data to generate personalized
21 outputs. Frischmann & Ormerod, *supra*, at 22. A smart thermostat, for instance, collects and
22 uses its owner’s personal data to predict the temperature that is best for them. *Id.* at 20. By
23 Plaintiffs’ logic, when the thermostat sets the temperature based on the owner’s personal data,
24 the thermostat company is saying, “This temperature takes into account your preferences,” so
25 any regulation of the company’s collection and use of personal data is subject to First
26 Amendment scrutiny. Similarly, a liquor store clerk who hands a minor a six pack of beer based
27 on the minor’s preference for something fruity could be understood to say, “You will find this
28 beer interesting,” so the sale of the beer should be protected by the First Amendment.

1 When personalization does communicate something, it isn't the sort of vague, generic
2 message that Plaintiffs claim they are sending, but a message in the speaker's own voice. In
3 cases where the Supreme Court has found the personalization of a product expressive, such as a
4 personalized wedding website, *303 Creative*, 600 U.S. at 587, and a personalized wedding cake,
5 *Masterpiece Cakeshop v. Colorado Civil Rights Commission*, 584 U.S. 617, 626 (2018), the
6 message the Court found expressive was not "this is the best website for you" or "you'll find
7 this cake interesting" but a message in the speaker's own voice: "This is a marriage I want to
8 celebrate." Similarly, in *Sorrell*, the pharmaceutical companies challenging a regulation of
9 physician prescribing data used that data to decide what words and ideas would best persuade
10 individual physicians to prescribe their drugs. U.S. 552 at 557–58. The companies' marketers
11 thus used the data not to say, "You may find this advertisement interesting," but to personalize a
12 message in their own voice along the lines of, "Prescribe Brand Name Drug X because it's more
13 effective than Drug Y you currently prescribe for Condition Z." Plaintiffs, meanwhile, are not
14 trying to persuade users to believe or do anything—besides stay on their platforms longer. And
15 while the Supreme Court found that personalization did not disqualify interactive video games
16 from being expressive, personalization *itself* was not the reason the games were expressive: it
17 was that the game creators "communicate ideas—and even social messages" through the game's
18 features and storytelling mechanics. *Brown v. Ent. Merchants Ass'n*, 564 U.S. 786, 790 (2011).

19 Personalization might also communicate something about the relationship between two
20 people, although not in the context of behavioral profiling for addictive feeds. A person who
21 picks out a gift for a friend that reflects the friend's interests does not say, through their gift-
22 giving, "This is something I think you will find interesting," but, instead, "I care about you."
23 Humans have limited time and attention, and devoting some of it to choosing a gift for a person
24 reflects the gift giver's feelings toward the person. Revenue-maximizing algorithms, deployed
25 at scale, do not express a similar message through their personalization, because the
26 personalization is, in fact, *impersonal*: it is performed by a computer, in a matter of moments,
27 with little marginal cost to the company, to benefit the company, not the user.

1 **C. The use of machine learning to behaviorally profile users further**
2 **undermines the expressiveness of the content decisions.**

3 When companies use behavioral profiling to generate personalized feeds, humans do not
4 dictate the rules for what to include and how to rank it. As discussed in Part I.B., companies use
5 machine learning to train their behavioral profiling algorithms. The companies give the
6 computer a goal—maximize time spent on the platform—and a set of potential parameters, and
7 let the machine make its own rules for what content to select and how to rank it. The machine
8 then executes the rules without human supervision. As a result, the human creators of the
9 algorithm cede their ability to control, explain, understand, or predict the algorithm’s output.
10 *See Moody*, 603 U.S. at 795 (Alito, J., concurring in the judgement) (contrasting newspaper
11 editors’ expressive curation with algorithms that “prioritize content based on factors that the
12 platforms have not revealed and may not even know.”); Mackenzie Austin & Max Levy, *Speech*
13 *Certainty: Algorithmic Speech and the Limits of the First Amendment*, 77 *Stan. L. Rev.* 1, 63–64
14 (2025).

15 This undermines a claim to protected editorial discretion. In editorial discretion cases,
16 the curator expresses themselves through the decision to publish or not publish something. If the
17 social media company delegates the decision-making process to an algorithm, it is not at all
18 clear that the decision can be attributed to the humans in the company. That is why at least four
19 justices and some scholars believe that the use of machine-learning algorithms may attenuate
20 the expressiveness even of *content moderation* decisions that otherwise have all the hallmarks
21 of editorial discretion.

22 Machine learning algorithms are inscrutable black boxes that create their own rules with
23 limited guidance from their human creators. Austin & Levy, *supra*, at 39–43. It is not clear that
24 every output of a machine learning algorithm reflects a human’s expressive choice such that the
25 output can be treated as the human’s speech, *id.* at 42–43, 79–81, and it would be a shocking
26 break from precedent to recognize that anything other than a human or a group of humans has
27 First Amendment rights. As Justice Barrett wrote in her concurrence, “technology may attenuate
28 the connection between content-moderation actions (e.g., removing posts) and human beings’

1 constitutionally protected right” of expression. *Moody*, 603 U.S. at 746 (Barrett, J., concurring).
2 She further noted, “If the AI relies on large language models to determine what is ‘hateful’ and
3 should be removed, has a human being with First Amendment rights made an inherently
4 expressive ‘choice . . . not to propound a particular point of view?’” *Id.*

5 The human creators of machine-learning algorithms are also not able to fully explain
6 why the algorithms make any given decision nor to predict with any level of certainty what the
7 algorithms will output in any given case. *See Austin & Levy, supra*, at 63–64. As Justice Alito
8 observed, “[W]hen AI algorithms make a decision, even the researchers and programmers
9 creating them don’t really understand why the models they have built make the decisions they
10 make. Are such decisions equally expressive as the decisions made by humans?” *Moody*, 603
11 U.S. at 795 (Alito, J., concurring in the judgement) (quotation marks and citations omitted). No
12 court has ever ruled that a speaker engages in editorial expression when they compile speech
13 using metrics that they can neither understand nor explain, *see Austin & Levy, supra* at 30–33,
14 and whose output they cannot control and must frequently disavow, *see, e.g., Jason Kohler,*
15 *Instagram ‘Error’ Turned Reels Into Neverending Scroll of Murder, Gore, and Violence,*
16 *404Media* (Feb. 27, 2025) (summarizing Meta’s apology for erroneously causing many users’
17 feeds to be filled with videos of humans and animals being violently killed).¹⁰

18 If the expressiveness of *content moderation* decisions can be attenuated by the use of
19 machine learning algorithms, then the case for the expressiveness of *behavioral profiling* using
20 machine learning is even weaker because such conduct lacks any characteristic of editorial
21 discretion. *See Part II.B.* There is also clear evidence that revenue-maximizing algorithms do
22 not reflect companies’ editorial judgment because they sometimes amplify media that violates
23 the company’s own content policies. *See, e.g., Sam Schechner, et al., How Facebook Hobbled*
24 *Mark Zuckerberg’s Bid to Get America Vaccinated*, *Wall St. J.* (Sep. 17, 2021).¹¹ This shows
25 that the people in the company lack control over what messages and viewpoints are selected by
26

27 ¹⁰ <https://www.techpolicy.press/an-advocates-guide-to-automated-content-moderation/>.

28 ¹¹ <https://www.wsj.com/articles/facebook-mark-zuckerberg-vaccinated-11631880296>.

1 the algorithm. When platforms lack curatorial control, they can hardly claim to be exercising
2 editorial judgement. It would be as if the parade committee in *Hurley* delegated authority to
3 choose parade units to a random unvetted third party, told them the only constraint was to
4 choose participants whose banners were eye-catching, and then tried to claim the third party's
5 curatorial decisions represented their own pro-Irish expression even when the third party placed
6 a float defaming Irish people at the vanguard of the parade.

7 But analogies between the decision making of machine-learning algorithms and that of
8 humans will inevitably be strained because the way that machine-learning algorithms make
9 decisions is so alien to human decision making. Humans may consider their audience when
10 making editorial choices, but unlike a machine-learning algorithm designed to behaviorally
11 profile users, humans cannot and do not consider information about the audience in a vacuum,
12 ignoring all information about the message, viewpoint, topic, or speaker of the content they
13 recommend. Librarians, for instance, do not mindlessly recommend books to children simply
14 because other children requested them. Librarians are trained professionals with advanced
15 degrees in vetting and recommending books and periodicals. American Library Ass'n, *Become*
16 *a Librarian*.¹² Their job is to know something about the expressive content of the materials they
17 recommend before recommending them, just as it is the job of a lawyer to know the holding of a
18 case they are citing before citing it. It is also impossible for a librarian to shield themselves from
19 information about the materials they recommend. Even just the title of a book can give the
20 librarian a good idea of its expressive content.

21 Librarians are a bad analogy to behavioral profiling algorithms for another reason: the
22 way a librarian gathers and uses information about a child is fundamentally different from how
23 a behavioral profiling algorithm gathers and uses personal data. A librarian does not surveil
24 children. They do not trail a child around the library measuring how long the child's eyes
25 dwelled on different book covers, group that child with other library-goers whose eyes dwelled
26 on similar covers, and then recommend a book to the child based on what those other library-

27
28 ¹² <https://www.ala.org/educationcareers/libcareers/become>.

1 goers checked out, no matter who the other library-goers were and without knowing anything
2 about the book in question. If that were how librarians worked, their actions would rightly be
3 condemned as invasive and be subject to regulation.

4 **D. Behavioral profiling is a functional, not expressive, aspect of feed creation.**

5 Courts have long recognized that some communications “combin[e] nonspeech and
6 speech elements, *i.e.*, functional and expressive elements.” *United City Studios, Inc. v. Corley*,
7 273 F.3d 429, 451 (2d Cir. 2001). This “de facto functionality doctrine” allows the “state to
8 regulate the functional aspects of the communication process, while protecting its expressive
9 aspects.” *Wu, supra*, at 1496–97. Behavioral profiling is a functional aspect of feed creation.
10 This functional aspect is not inextricably intertwined with the expressive aspects of feed
11 creation. The State can regulate the use of behavioral-profiling algorithms without impacting a
12 company’s ability to select and rank content based on a company’s views about the messages
13 expressed.

14 First Amendment doctrine has long recognized that conduct can contain both speech and
15 nonspeech elements. *See O’Brien*, 391 U.S. at 376; *see also Clark v. Cmty. for Creative Non-*
16 *Violence*, 468 U.S. 288, 296 (1984) (enforcement of a no-camping-in-the-park law targeted the
17 “facilitative” aspect of a protest). “When speech has both protected and unprotected features . . .
18 ‘the unprotected features of the [speech] are, despite their [communicative] character,
19 essentially a ‘nonspeech’ element’ for purposes of the First Amendment.” *Free Speech Coal.,*
20 *Inc. v. Paxton*, 606 U.S. 461, 492 (2025) (quoting *R.A.V. v. St. Paul*, 505 U.S. 377, 386 (1992)).
21 In a First Amendment challenge, then, courts do not just look at whether the conduct being
22 regulated has *some* expressive element, but whether the specific practice that is regulated is
23 expressive or non-expressive.

24 When considering limits on the distribution and use of computer code, courts have long
25 focused on whether the law at issue regulates the expressive or the functional aspect of the code.
26 *See Kyle Langvardt, Crypto’s First Amendment Hustle*, 16 *Yale J.L. & Tech.* 130, 146 (2023).
27 The distribution of code is expressive when the code is “meant to be read and understood by
28 humans” and when it communicates the “scientific ideas” of the programmer to others.

1 *Bernstein v. Dep't of Justice*, 176 F.3d 1132, 1142, 1145 (9th Cir. 1999), *reh'g granted, op.*
2 *withdrawn*, 192 F.3d 1308 (9th Cir. 1999). A use of code is functional when the code is instead
3 used to accomplish the task that the software was programmed to achieve. *Corley*, 273 F.3d at
4 451. For example, when a researcher distributes code to communicate to other researchers how
5 to design an encryption algorithm, such a use of code is expressive. *Bernstein*, 176 F.3d at 1141.
6 But when a person distributes encryption software to an end user to decrypt an encrypted file,
7 that use is functional. *Corley*, 273 F.3d at 451, 454. If a law regulates a functional aspect of
8 code, courts determine whether the regulation would have an incidental impact on an expressive
9 aspect of the code, and if so, subject the regulation to intermediate scrutiny. *See id.* at 454.

10 Similarly, courts have recognized that architecture combines both expressive and
11 functional activities. *See, e.g., Committee for Reasonable Regulation of Lake Tahoe v. Tahoe*
12 *Regional Planning Agency*, 311 F. Supp. 2d 972, 1005 (D. Nev. 2004) (noting that while a
13 building project “may involve an intent to convey an artistic, political, or self-expressive
14 message, the great majority [of building choices] are functional in nature and are not commonly
15 associated with expression”). Whether a regulation of building practices triggers First
16 Amendment scrutiny depends not on whether any aspect of building design is expressive (some
17 of it surely is, such as the choice of Beaux-Arts or Brutalism) but on what aspect of the building
18 process is being regulated and whether that aspect has the characteristics of expressive conduct.
19 *See Burns v. Town of Palm Beach*, 999 F.3d 1317, 1335–43 (11th Cir. 2021), *cert. denied*, 142
20 S. Ct. 1361 (2022).

21 When social media companies use surveillance data to make curatorial decisions, they
22 are not trying to—nor do they actually—send their own ideas or messages to the user. *See Part*
23 *II.B.* Their behavioral profiling algorithms, instead, serve the functional purpose of organizing
24 the media on a platform in a way that maximizes the amount of time users spend on the
25 platform, which maximizes corporate profits. *See Richards & Hartzog, supra*, at 1162–63.

26 While companies may combine expressive content moderation with non-expressive
27 behavioral profiling to create a single feed, regulation of the latter does not impact the former.
28 The two are entirely separate processes. A company could re-engineer a feed to not use the

1 surveillance data without changing their content moderation practices. *See* Mark Zuckerberg, *A*
2 *Blueprint for Content Governance and Enforcement*, Facebook (May 5, 2021) (discussing
3 content moderation and engagement maximization as independent processes);¹³ *NetChoice I*,
4 761 F.Supp.3d at 1223 (“if it is very easy to separate an algorithm's expressive content
5 moderation functions from non-expressive user-activity-based functions, a law prohibiting
6 personalized feeds from relying on user activity information may also only incidentally burden
7 speech. A covered company could just remove the user activity factors from the
8 recommendation algorithms driving its media feeds.”) The feed would be just as expressive
9 after that change because behavioral profiling is not responsible for the curation’s
10 expressiveness—content moderation is.

11 CONCLUSION

12 For the foregoing reasons, *amici* ask this Court to deny Plaintiffs’ requests for
13 preliminary injunctions.

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Respectfully submitted,

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¹³ <https://www.facebook.com/notes/751449002072082>.