PSG

SILENCE

panorama-sg.com

ISSN 3054-4386
Publisher: Panorama Scholarly Group

Vol. 1, No.1, 78-89, 2026
DOI:10.5281/zenodo.20625002

Quiet Research

Algorithmic Silence as Cultural Governance: Platform Visibility, AI-Generated Chinese Digital Content, and the Unfinished Politics of Cultural Legitimacy

Haoyang He[1*]

[1] *Department of Communication, Faculty of Humanities and Social Sciences, Beijing Normal–Hong Kong Baptist University, Zhuhai, China*
[*] *Corresponding author*

Corresponding author:
s230031072@mail.bnbu.edu.cn

Received: 1 May 2026
Accepted: 2 June 2026
Available online: 20 June 2026

Abstract
This article develops algorithmic silence as a concept for studying how platform visibility governs the circulation and legitimacy of AI-generated Chinese digital content. Whereas existing debates often treat visibility as distribution, popularity, or exposure, the article argues that visibility has become a managed condition through which cultural works become discoverable, rankable, measurable, interpretable, and institutionally recognizable. Drawing on 30 anonymized semi-structured interviews, 178 coded interview excerpts, 240 platform observation records, a 20-code qualitative codebook, and reflexive audit materials, the article examines how recommendation uncertainty, metric hierarchies, template aesthetics, AI labeling, institutional risk management, and unstable platform traces produce forms of silence that do not require explicit deletion or prohibition. The analysis identifies five linked dimensions of algorithmic silence: infrastructural, metric, aesthetic, institutional, and methodological silence. It further proposes slow visibility as a counter-concept for cultural expression whose value depends on time, context, community interpretation, or non-metric recognition. The article contributes to platform studies by reframing visibility as cultural governance, to AIGC studies by foregrounding human-AI co-production and legitimacy struggles, and to methodological debates by showing why partial and unstable traces must be handled through causal restraint. The study does not claim direct access to platform algorithms; instead, it offers an evidence-bounded account of how managed visibility reorganizes cultural recognition.

Keywords: algorithmic silence; platform visibility; AIGC; Chinese digital culture; cultural legitimacy; methodological transparency; slow visibility

1. Introduction: From Platform Visibility to Algorithmic Silence

AI-generated Chinese digital content now circulates inside environments where cultural expression is not simply published and then judged by audiences. It enters infrastructures that sort, recommend, rank, label, archive, monetize, and sometimes withhold attention before cultural evaluation becomes visible. For creators, the practical question is rarely whether an AI-assisted image, video, remix, or essay can technically be generated. The harder question is whether the work can become findable, interpretable, trusted, and durable within platform conditions that remain opaque to both creators and researchers. This article begins from that problem. It asks what happens when visibility itself becomes a cultural gate rather than a neutral channel of distribution.

Platform studies has established that platforms are not passive intermediaries. They organize markets, publics, cultural commodities, labor practices, data flows, and governance relations [16, 20, 27, 29, 34]. Yet a recurring weakness in discussions of digital cultural production is that visibility is often treated as a measurable outcome: more views, more likes, higher ranking, greater circulation. Such metrics matter, but they do not simply describe cultural attention. They produce conditions under which some forms of cultural work become legible as valuable while others remain weakly recommended, difficult to search, hard to archive, or institutionally unrecognized. In algorithmic culture, the relevance of algorithms lies not only in what they calculate but in how they shape the categories through which content can matter [17,31].

The context of Chinese digital platforms is especially important because AI-generated content is developing within a dense ecology of short-video platforms, social commerce, entertainment infrastructures, regulatory expectations, creator economies, and institutional branding practices. Douyin, Xiaohongshu, Bilibili, Kuaishou, and Weibo do not offer one unified visibility regime. They organize different relationships among recommendation, search, topic ranking, content labels, creator guidance, institutional accounts, and everyday audience interpretation, including influencer-oriented and purchase-related uses of Douyin that have been studied through user motivation and parasocial perspectives [35]. Existing research on China's platform ecology has shown that creators learn to imagine and adapt to platform logics, that governance may operate through playful or indirect interfaces, and that platform capitalism in China has regional and historical specificity [24,25,36,37]. AIGC intensifies these questions because AI output can be celebrated as innovation, suspected as derivative, marked through labels, flattened through templates, or excluded from serious cultural recognition.

This article develops algorithmic silence to name this condition. Algorithmic silence refers to a platform-mediated condition in which cultural content, creators, styles, communities, or questions are not necessarily banned or removed, but are rendered less visible, less legible, less recommendable, less searchable, less measurable, less archivable, or less institutionally recognizable. The concept is not a synonym for censorship. It directs attention to quieter and often ambiguous forms of managed visibility: weak recommendation, unstable search results, shifting labels, low metric recognition, aesthetic standardization, institutional preference for safe innovation, and the difficulty of reproducing personalized platform traces.

The article is organized around four research questions. RQ1 asks: How does platform visibility operate as a form of cultural governance in the circulation of AI-generated Chinese digital content? RQ2 asks: Through what infrastructural, metric, aesthetic, institutional, and methodological mechanisms is algorithmic silence produced? RQ3 asks: How does algorithmic silence reshape the cultural legitimacy of AIGC creators, texts, audiences, and institutions? RQ4 asks: How can researchers responsibly study platform-mediated invisibility when the relevant data are partial, unstable, personalized, or inaccessible? These questions are not designed to prove a single hidden algorithmic cause. They build a cautious, evidence-bounded account of visibility as a distributed governance relation.

The article contributes in three ways. First, it contributes to platform studies by shifting the analytical focus from visibility as exposure to visibility as governance. Second, it contributes to AIGC research by showing that legitimacy is negotiated not only through authorship or authenticity but also through platform-readable signals, institutional risk calculations, and the invisibility of human labor behind AI output. Third, it contributes to research methodology by treating personalized feeds, unstable traces, screenshots without context, non-replicable searches, and incomplete archives as conditions that must shape how claims are made. The article proceeds through a literature review, a five-dimensional theoretical framework, a data-integrated methodology, four analytical sections corresponding to the research questions, and a discussion of slow visibility as an alternative politics of cultural recognition.

2. Literature Review: Why Visibility Has Been Over-Trusted

2.1. Platform Visibility and Algorithmic Mediation

Platform studies has repeatedly challenged the idea that platforms merely host user expression. Platforms make web data platform-ready, structure social media logics of programmability and popularity, and transform cultural commodities through contingent and datafied infrastructures [20,27,34]. For this article, platform visibility names the organized condition through which content becomes discoverable, rankable, measurable, circulatable, interpretable, and culturally recognizable. It is therefore not identical with audience attention; it is the infrastructure through which attention becomes possible and countable.

Studies of algorithmic power show that ranking and recommendation systems operate through uncertainty. Bucher [9] described the "threat of invisibility" as a central form of algorithmic power, while Bucher [10] conceptualized the algorithmic imaginary as the way users interpret and feel algorithmic systems in everyday life. Beer [2] similarly argued that algorithms possess social power through classifications and anticipations. These arguments matter for AIGC because creators often infer platform preferences without access to ranking systems. They adjust titles, covers, tags, disclosure wording, posting time, and visual style not because they know the algorithm, but because visibility is experienced as a field of uncertain consequences.

If visibility is treated only as an outcome, low visibility appears as failure, irrelevance, or weak audience interest. If it is treated as governance, the question changes: which forms of cultural expression are easier to rank, recommend, stabilize, explain, and recognize, and which forms become difficult to sustain? This shift provides the theoretical ground for the concept of algorithmic silence developed in the next section.

2.2. AIGC and the Crisis of Cultural Legitimacy

AIGC research often centers on authorship, creativity, automation, and the boundaries of human agency. Boden [5] argued that creativity and artificial intelligence require careful conceptual distinction rather than simple opposition. Contemporary generative AI intensifies that problem because systems can now produce text, images, video, music, scripts, and hybrid formats at scale. Floridi and Chiriatti [15] emphasized the scope and limits of large language models, while Dwivedi et al. [14] mapped the opportunities and risks of generative conversational AI for research, practice, and policy. These debates are cultural as well as technical: they concern how value is recognized when the boundaries among author, tool, model, dataset, prompt, editor, platform, and audience become unstable.

Cultural legitimacy is used here in a focused sense: the process through which cultural forms, creators, practices, and texts become recognized as valuable, authentic, creative, professional, representative, or worthy of circulation. Sociological accounts of legitimacy and valuation show that recognition is organized through fields, institutions, categories, and evaluative devices rather than naturally given [6,21,23,32]. In AIGC, legitimacy becomes fragile because audiences may treat AI output as technically impressive but culturally thin; institutions may embrace polished and safe works while avoiding ambiguous or context-heavy work; and creators may find that prompting, editing, selection, and cultural translation remain invisible. Recent work on generative AI and creative industries warns that automation narratives can erase human creative labor [3].

The empirical question, then, is not whether AI-generated content is legitimate or illegitimate as such. It is how legitimacy is filtered through labels, metrics, templates, institutional uptake, and audience suspicion. This article links that question to platform visibility: AIGC becomes culturally recognizable only through infrastructures that also sort, measure, and sometimes attenuate it.

2.3. Content Moderation, Opaque Governance, and Platform Power

Platform governance includes rules, policies, content moderation, ranking systems, labels, recommendation architecture, creator guidance, and institutional accountability. Gorwa [18] defined platform governance as the systems through which platforms structure behavior and content, while Gorwa et al. [19] showed that algorithmic content moderation combines technical and political challenges. The transparency ideal is limited: seeing more information about a system does not necessarily produce accountability if users, researchers, or publics cannot interpret how decisions are made [1].

Content moderation and ranking opacity matter here because silence often occurs without a clear decision point. A work may remain under review, receive an AI-generated label, disappear from search, lose recommendation share, or become difficult to retrieve without being formally removed. Burrell [11] and Kitchin [22] caution that algorithmic systems can be opaque at technical, institutional, and epistemic levels. In creator cultures, opacity becomes practical knowledge. Creators learn through rumor, comparison, experimentation, and peer talk, a dynamic described as algorithmic gossip on YouTube and as a visibility game among influencers [4, 12].

In China's platform context, governance also operates through localized platform designs and cultural expectations. Douyin's content ecosystem is shaped by recommendation, entertainment, commerce, and governance interfaces; studies of Douyin have shown that creator imaginaries and platform moderation are inseparable from everyday production [24, 36]. For AIGC, AI labels, disclosure norms, template aesthetics, and policy-sensitive adaptation all participate in the organization of what can be seen, counted, trusted, and repeated.

2.4. Silence, Absence, and Methodological Uncertainty

Silence is difficult to study because it does not always leave a stable object. In platform research, absence may take the form of search instability, weak recommendation, disappearing comments, expired links, incomplete screenshots, personalized feeds, or content that never becomes visible enough to enter a dataset. Methodological debates on algorithmic accountability and auditing emphasize that computational systems are difficult to investigate without access to internal data, controlled conditions, or robust comparison points [13, 26]. Rieder et al. [30] showed that ranking cultures can be studied through search result modulation, but such work also demonstrates that visibility is volatile and situated.

This volatility requires methodological humility. Qualitative platform research cannot always reproduce the exact feed encountered by a creator, viewer, or institution. It can, however, analyze how participants experience opacity, how traces become incomplete, how researchers triangulate screenshots with interviews and codebooks, and how causal claims should be limited. Braun and Clarke's reflexive thematic analysis emphasizes that qualitative analysis is interpretive rather than mechanical [7, 8]. Tracy's [33] criteria for qualitative quality and Nowell et al.'s [28] discussion of trustworthiness are useful because they shift the focus from impossible total transparency to credible, reflexive, and auditable analytic practice.

Methodological silence is therefore kept as a supporting concept rather than a second thesis. It names the difficulty of observing personalized feeds, unstable searches, disappearing traces, and inaccessible recommendation pathways. This condition does not license speculation. It requires an evidence hierarchy, explicit audit trails, and a refusal to convert every instance of invisibility into proof of suppression.

3. Theoretical Framework: Algorithmic Silence as Cultural Governance

The conceptual hierarchy of the article is deliberately narrow. The first-level concept is algorithmic silence. Platform visibility and cultural legitimacy are second-level concepts that explain how silence becomes possible and why it matters. Slow visibility and methodological silence are third-level concepts: they clarify the normative and methodological implications of the argument without displacing the central concept.

Algorithmic silence refers to a platform-mediated condition in which cultural content, creators, styles, communities, or questions are not necessarily banned or removed, but are rendered less visible, less legible, less recommendable, less searchable, less measurable, less archivable, or less institutionally recognizable. The concept has three implications. First, silence can occur without deletion. Second, it can operate through ordinary platform functions such as ranking, metrics, labels, search, and recommendation. Third, it is relational: it emerges among infrastructures, creators, audiences, institutions, and researchers rather than from a single technical cause.

Platform visibility is the condition through which content becomes discoverable, rankable, measurable, circulatable, interpretable, and culturally recognizable. Cultural legitimacy is the process through which cultural forms, creators, practices, and texts become recognized as valuable, authentic, creative, professional, representative, or worthy of circulation. Slow visibility describes cultural expression whose value requires time, interpretation, context, community memory, or non-metric recognition. Methodological silence refers to the researcher's partial access to personalized, unstable, or disappearing traces.

The framework has five dimensions. Infrastructural silence refers to weak recommendation, unstable searchability, ranking opacity, non-archival traces, and moderation ambiguity. Metric silence refers to the conversion of likes, shares, completion rates, views, saves, and ranking positions into proxy indicators of cultural value. Aesthetic silence refers to the normalization of fast, legible, template-like, and visually standardized forms. Institutional silence refers to the selective recognition of safe, polished, explainable, and low-risk AIGC by brands, media, schools, cultural organizations, and platforms. Methodological silence refers to the researcher's partial access to personalized, unstable, or disappearing traces. Figure 1 presents these dimensions as connected dimensions of managed visibility rather than as a linear sequence.

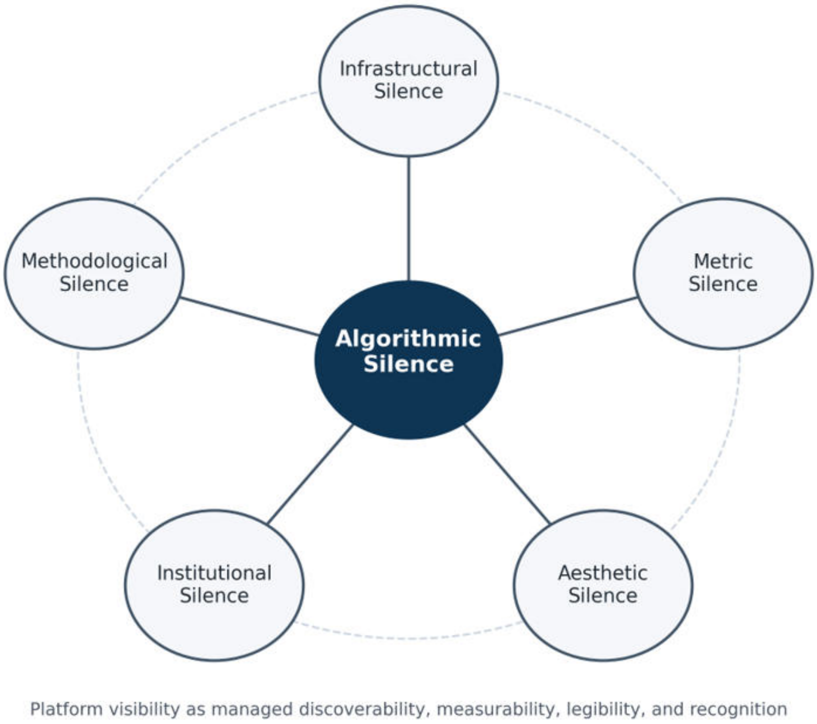

Figure 1. Five-Dimensional Model of Algorithmic Silence as Cultural Governance.

4. Methodology: Data-Integrated Reverse Review and Reflexive Platform Analysis

4.1. Research Design

The study uses a data-integrated reverse review design. A reverse review begins from a conceptual problem that visibility-based research may naturalize: the assumption that visible content provides an adequate map of cultural value. Instead of asking only what becomes popular, the analysis asks how platform conditions make some cultural forms more rankable, searchable, measurable, and institutionally legible than others. The design is conceptual-methodological because it develops algorithmic silence as a framework, and empirical because the framework is grounded in anonymized interviews, coded excerpts, platform observation records, coding matrices, and reliability/audit documents.

The empirical materials consist of 30 semi-structured interviews, 178 coded interview excerpts, 240 post-level platform observations, a 20-code qualitative codebook, interview memos, a coding matrix, a theme-evidence map, a reliability/audit sheet, and a data dictionary. Interviews were conducted from January 10, 2026, to April 9, 2026; platform observations cover posts dated from August 2, 2025, to April 16, 2026. The interview sample includes 10 AIGC creators, 7 viewers/ordinary users, 5 brand or cultural-institution workers, 4 researchers/critics, and 4 MCN or platform operators. Primary platform contexts include Kuaishou (8), Weibo (8), Douyin (7), Xiaohongshu (4), and Bilibili (3). The platform observation records cover Douyin (86), Xiaohongshu (76), Bilibili (39), Kuaishou (23), and Weibo (16).

Because the research question concerns invisibility, the study does not attempt to reconstruct platform algorithms. It triangulates participants' accounts of visibility uncertainty, coded thematic patterns, post-level observation variables, and published scholarship. This interpretive strategy supports claims about how visibility is experienced, coded, institutionally interpreted, and methodologically constrained; it does not support claims about hidden ranking weights, proprietary moderation thresholds, or definitive algorithmic intent.

4.2. Data Sources, Evidence Status, and Traceability

The evidence base was organized into four layers. The first layer is the interview sample and interview excerpts. The interviews produced 1,967 total minutes of interview material, with a mean interview length of 65.6 minutes. The excerpt sheet includes Chinese-language quotations, English analytical translations, interpretive memos, evidence strength scores, code IDs, and code families. The second layer is the codebook and coding matrix, which define 20 codes across infrastructural, metric, aesthetic, institutional, methodological, reflexive, slow-visibility, creator-practice, audience-reception, and human-AI co-production dimensions. The third layer is the platform observation dataset, which records platform, content type, AIGC method, disclosure mode, engagement indicators, search and recommendation shares, visibility score, stability index, moderation/label status, dominant silence form, and analytic note. The fourth layer is the theme-evidence map and reliability/audit sheet. Interview participant identities, direct account identifiers, post URLs, and potentially identifying contextual details are not reported. Platform observation values are used in aggregated and interpretive form because visibility traces are sensitive, unstable, and platform-specific. The manuscript uses selected quotations and summary statistics, but it does not reproduce the full dataset. Table 1 summarizes the empirical components, analytical uses, and reporting constraints.

Table 1. Data Sources, Evidence Status, and Reporting Constraints

Data component	Empirical scope	Analytical use	Reporting constraint
Interview sample	30 anonymized participants: AIGC creators, viewers, brand/cultural-institution workers, researchers/critics, and MCN or platform operators.	Sample structure and role/platform comparison.	Report generalized roles and participant IDs only.
Interview excerpts	178 coded excerpts with Chinese originals, English analytical translations, code IDs, and interpretive memos.	Thematic evidence for RQ1–RQ4.	Use selected excerpts; interpret each quotation analytically.
Codebook and coding matrix	20 qualitative codes across infrastructural, metric, aesthetic, institutional, methodological, reflexive, slow-visibility, creator-practice, audience-reception, and co-production dimensions.	Code family construction and evidence-to-RQ mapping.	Do not treat codes as automatic proof; retain interpretive context.
Platform observations	240 post-level observations from Douyin, Xiaohongshu, Bilibili, Kuaishou, and Weibo.	Contextualize visibility, disclosure, label, search, recommendation, and stability patterns.	Use aggregated and cautious interpretation; no proprietary algorithmic causality.
Theme and reliability audit	Five theme-evidence mappings; mean agreement 0.89; mean kappa 0.74.	Audit trail for credibility and causal restraint.	Use as transparency support, not as mechanical validity guarantee.

Note. The table clarifies how each component is used while preserving participant confidentiality and platform-trace sensitivity.

Interview excerpts are presented in Chinese with analytical English translations. Quotations have been minimally edited only to remove verbal fillers or identifying details, without altering substantive meaning. The translations are interpretive rather than literal and are used to clarify analytical relevance. Participant identities, account identifiers, URLs, and contextual details that may enable deductive identification have been withheld. This approach balances evidentiary traceability with confidentiality and platform-trace sensitivity.

The reliability/audit material reports a mean percent agreement of 0.89 and a mean kappa value of 0.74 across the 20-code coding audit. These indicators are not treated as proof of mechanical objectivity. They are used as evidence of coding consistency and as an audit trail for how the code families were applied. Because the analysis is interpretive, the primary standard is analytic transparency: codes must be defined, inclusion and exclusion rules stated, excerpts interpreted, and claims kept within the evidence provided.

4.3. Qualitative Coding Procedure

The coding process followed a reflexive thematic logic. Initial coding identified recurring phrases and experiences related to recommendation uncertainty, search instability, metric substitution, AI-label effects, institutional filtering, template normalization, creator adaptation, human-AI labor, audience authenticity suspicion, and methodological uncertainty. Focused coding then grouped these experiences into code families. For example, INF_RANK, INF_SEARCH, INF_ARCH, and INF_MOD were grouped under infrastructural silence because each concerns the technical and governance conditions through which visibility becomes unstable or ambiguous. MET_PROXY and MET_LOW were grouped under metric silence because they concern the substitution of platform indicators for cultural judgment and the persistence of value in low-metric works.

Inclusion and exclusion rules were crucial. Ranking opacity was coded only when participants discussed recommendation, traffic allocation, ranking drops, or inconsistent exposure as uncertain or opaque; generic low popularity was excluded. Search instability was coded only when retrievability changed across time, account, or device; ordinary search optimization advice was excluded. Metric proxy was coded when metrics substituted for evaluation, not when metrics were merely reported. Methodological silence was coded when participants or researcher memos explicitly addressed partial traces, personalization, causal uncertainty, or non-reproducibility. This distinction prevents the analysis from turning every weakly visible work into evidence of algorithmic suppression.

The coding matrix was then compared with the theme-evidence map. Five themes emerged: visibility as governance; mechanisms of algorithmic silence; legitimacy after platform mediation; methodological transparency; and slow visibility as a counter-concept. These themes correspond to the four research questions. RQ1 is addressed through ranking, metrics, and creator adaptation. RQ2 is addressed through infrastructural, metric, aesthetic, institutional, and methodological mechanisms. RQ3 is addressed through audience authenticity judgments, AI-label effects, institutional filtering, context loss, and human-AI co-production. RQ4 is addressed through personalization, trace incompleteness, causal restraint, and unresolved uncertainty.

4.4. Platform Trace Analysis Logic

The platform observation dataset is used to contextualize, not deterministically prove, participants' accounts. The 240 records cover five platforms and ten content types, including AI music remix, AI virtual influencer posts, AI image carousels, AI-scripted explainers, AI local-culture documentary clips, AI avatar commentary, AI heritage short videos, AI product-cultural crossover posts, AI poem/essay videos, and AI meme remixes. The AIGC methods include voice cloning/synthesis, multimodal workflows, text-to-video, prompted scriptwriting, image generation, AI-assisted editing, and avatar generation. Disclosure modes include explicit AI disclosure, platform label only, watermark, ambiguous disclosure, and no disclosure.

The trace variables allow cautious comparison among visibility score, stability index, search view share, recommendation view share, moderation or label status, and dominant silence form. A post may be measurable but weakly searchable; searchable but low in recommendation share; recommended but institutionally distrusted; or high-performing but aesthetically flattened. The dataset therefore supports relational interpretation rather than causal attribution.

Platform traces are limited by temporality. A screenshot, metric capture, or post-level observation describes a situated moment, not a total platform state. Personalized feeds, device settings, geographic differences, account histories, and changing moderation states all limit reproducibility. For this reason, the analysis treats platform trace variables as evidence of visibility conditions and methodological challenges, not as direct windows into proprietary ranking systems.

4.5. Researcher Reflexivity and Causal Restraint

This study adopts causal restraint as a methodological principle. It does not claim that a platform intentionally silenced a specific post, that low engagement proves suppression, or that every standardized aesthetic form is algorithmically determined. Such claims would exceed the available evidence. The analysis instead asks how creators, audiences, institutions, and researchers encounter conditions in which visibility is unevenly organized and difficult to interpret.

Reflexivity is important because the object of study is partly unavailable. The researcher can collect interviews, observation records, screenshots, codebooks, and memos, but cannot fully reconstruct personalized recommendation pathways or internal moderation rules. The manuscript therefore distinguishes between claims supported by the evidence and overclaims that must be avoided. For example, the evidence supports the claim that participants experience search and recommendation as unstable; it does not support the claim that a specific platform deliberately demoted a given cultural form.

4.6. Ethics, Anonymization, and Consent

All interview materials used in the manuscript are anonymized. Participants are identified only by participant codes such as P01 or P20, with generalized role labels where necessary to avoid deductive identification. Participants were informed of the research purpose, and no personally identifiable information is reported.

Platform observation materials are summarized or aggregated to avoid exposing account identities, URLs, or sensitive traces. Because the study concerns visibility, the ethics of reporting are especially important: reproducing platform traces too specifically could increase exposure for creators whose work is already vulnerable to unstable circulation. The manuscript therefore prioritizes analytical transparency without making the raw dataset publicly available.

5. Findings / Analysis I: Visibility as Governance

This section addresses RQ1 by showing how platform visibility conditions which AIGC works can become discoverable, measurable, interpretable, and legitimate. The interviews show that creators and institutional actors rarely describe visibility as a simple response to quality. They describe it as an uncertain field in which ranking, metrics, platform labels, and adaptation shape what kinds of cultural expression become viable.

P01, an AIGC creator active on Kuaishou, described search as a shifting condition rather than a stable access point. The participant was not claiming to know how the search system worked internally; the experience was one of practical uncertainty when the same cultural keyword behaved differently across accounts.

> *When I search the same AI Chinese-style keyword with another account, the results are completely different.*
>
> — P01, age 25, gender not disclosed, AIGC creator, Kuaishou

The empirical significance of this account lies in its ordinary frustration. Search is not experienced as a neutral database query but as a situated and personalized route into cultural visibility. The theoretical point follows from the experience: retrievability is one of the conditions through which AIGC becomes findable or forgettable.

P04, a researcher/critic working primarily with Douyin materials, described a different but related form of adjustment. The problem was not only what the platform might do after publication, but how anticipated recommendation shaped the creator's initial framing of the work.

> *I now first think about whether the title will be recommended, not how the story should be told.*
>
> — P04, age 35, male, researcher/critic, Douyin

The quotation shows visibility entering production before circulation occurs. The creator does not simply respond to platform performance after the fact; the anticipated ranking environment becomes part of the creative decision. This confirms the relevance of Bucher's [10] algorithmic imaginary and Cotter's [12] visibility game while extending them to AIGC cultural production.

The platform observation data align with these accounts. The trace dataset records disclosure mode, recommendation share, search share, visibility score, stability index, moderation/label status, and dominant silence form across 240 AIGC posts. The dominant silence forms include template visibility, infrastructural silence, platform visibility, metric silence, AI-label legitimacy effect, aesthetic silence, search instability, and slow visibility. A post can be highly visible through template conformity while remaining culturally thin; another can be culturally dense but weakly searchable or unstable over time.

Metric governance is particularly visible in institutional settings. P02, a brand/cultural-institution worker who evaluates AIGC content in relation to Douyin, described a familiar shift from creative language to performance language.

> *People say they value creativity, but in the end they ask about views, completion rate, and follower growth.*
>
> — P02, age 25, female, brand/cultural institution worker, Douyin

The statement does not dismiss metrics; it shows how metrics become institutional shortcuts. Views, completion rates, and follower growth make uncertain cultural value easier to justify to collaborators, organizations, and clients. This is where visibility becomes governance: it translates evaluation into a format that institutions can compare and defend.

P20, an AIGC creator on Kuaishou, made the consequence more direct. For this participant, a work without metrics remained present as a file or post but absent from collaboration and circulation.

> *If an AI work has no metrics, it almost does not exist in collaborations and reposting.*
>
> — P20, age 34, female, AIGC creator, Kuaishou

The phrase "almost does not exist" is analytically important because it describes a social rather than material disappearance. The answer to RQ1 is therefore bounded: platform visibility governs not by fully determining cultural value, but by conditioning the routes through which value becomes socially available. Recommendation, searchability, metric legibility, labels, and creator adaptation establish a practical environment in which some AIGC works become easier to recognize than others.

6. Findings / Analysis II: Mechanisms of Algorithmic Silence

This section addresses RQ2 by identifying five mechanisms through which algorithmic silence is produced: ranking without explanation, moderation without stable interpretability, searchability without archival reliability, engagement without cultural depth, and recognition without representational equality. Table 2 summarizes the evidence logic and the limits of causal claims.

Table 2. Mechanisms of Algorithmic Silence and Evidence Logic

Mechanism	Code family	Platform manifestation	Cultural effect	Allowed claim	Overclaim avoided
Ranking without explanation	Infrastructural Silence / Creator Practice	Unexplained traffic shifts, ranking drops, recommendation uncertainty.	Creators pre-optimize titles, covers, tags, and disclosure wording.	Visibility uncertainty shapes creator practice.	A platform deliberately suppressed a specific post.
Moderation without stable interpretability	Infrastructural / Institutional Silence	Under review, AI labels, warnings, limited reach, ambiguous safety signals.	Creators and institutions avoid risky or hard-to-explain themes.	Ambiguity shapes risk management.	Every avoided topic was formally banned.
Searchability without archival reliability	Infrastructural / Methodological Silence	Results shift across time, account, and device; links become hard to recover.	Low-visibility works become difficult to document later.	Retrievability is unstable and culturally consequential.	Search instability proves intentional erasure.
Engagement without cultural depth	Metric / Aesthetic Silence	Template hooks, standardized AI faces, high engagement indicators.	Cultural nuance is compressed into immediately legible signs.	Platform legibility can reward standardized forms.	All popular AIGC is culturally shallow.
Recognition without representational equality	Institutional Silence / Audience Reception	Safe, polished, easily branded AIGC receives institutional uptake.	Less legible or context-heavy work remains weakly recognized.	Recognition is unevenly filtered through safety and explainability.	Institutions reject all difficult culture.

Note. Evidence source for all rows: interviews; coding matrix; observation variables; moderation fields; aesthetic codes; institutional excerpts; theme map. The table distinguishes claims supported by the empirical materials from claims that would require platform-internal audit access or experimental evidence.

6.1. Ranking Without Explanation

Ranking without explanation appears when creators observe unstable exposure without a transparent account of why a work circulates or stalls. In the codebook, ranking opacity is defined as unexplained recommendation, traffic allocation, ranking drops, or inconsistent exposure. The mechanism is not simply low visibility. It is low or changing visibility under conditions where participants cannot distinguish audience preference, platform recommendation, content label effects, or timing.

The empirical consequence is anticipatory adjustment. Creators pre-optimize titles, covers, opening seconds, tags, posting routines, and AI disclosure wording before platform evaluation occurs. This does not mean that algorithms directly command creators. It means that creators work within an imagined platform environment where visibility uncertainty becomes a production constraint.

6.2. Moderation Without Stable Interpretability

Moderation without stable interpretability appears when platform labels, review states, content warnings, or limited reach signals are hard to read. The code INF_MOD captures references to under-review states, uncertain safety flags, and ambiguous governance signals. Participants did not only fear deletion. Several described the uncertainty of being reviewed, labeled, or weakly distributed without a stable reason. This aligns with scholarship on algorithmic content moderation as both technical and political [19].

The empirical consequence is policy-sensitive adaptation. Participants reported avoiding historically complex, identity-sensitive, or difficult-to-explain themes not always because those themes were prohibited, but because they were hard to predict within moderation and institutional environments. The responsible claim is that moderation ambiguity shapes creative risk management; the overclaim avoided is that every avoided topic was explicitly banned.

6.3. Searchability Without Archival Reliability

Searchability without archival reliability appears when content can be found at one moment but not another, or when low-visibility posts become practically unrecoverable. P28, an ordinary viewer on Kuaishou, framed the issue less as censorship than as the gradual disappearance of recoverability.

Many low-traffic works are not meaningless, but after several weeks even the link becomes hard to retrieve.

— P28, age 19, female, viewer/ordinary user, Kuaishou

The account links cultural value to archival fragility. The work is not necessarily deleted, but it becomes difficult to recover, cite, compare, or include in a later account of cultural production. For researchers, platform culture is therefore partly composed of traces that vanish from view before they can be systematically studied.

6.4. Engagement Without Cultural Depth

Engagement without cultural depth appears when metrics reward immediately legible forms while discouraging contextual density. P01, speaking as a creator rather than a distant observer, described the pressure through concrete elements of AI short-video style.

AI short videos increasingly look the same: a three-second hook, glowing transitions, and a generic Chinese-style face.

— P01, age 25, gender not disclosed, AIGC creator, Kuaishou

The quotation identifies a specific aesthetic pressure rather than condemning short video as a form. Cultural depth is not removed; it is compressed, flattened, or converted into decorative signs that can be recognized quickly. Engagement metrics may still rise, but the relation between metric success and cultural depth becomes unstable.

6.5. Recognition Without Representational Equality

Recognition without representational equality appears when institutions selectively legitimate AIGC that looks safe, polished, technological, and easy to explain. P02 condensed this institutional preference into the phrase "safe innovation."

Institutions like "safe innovation": it should look technological at first glance but not require too much explanation.

— P02, age 25, female, brand/cultural institution worker, Douyin

The empirical point is selective recognition. Institutions may publicly support AI creativity while avoiding works that require historical, local, dialectal, political, or community-specific interpretation. The result is not a simple rejection of AIGC, but a narrowing of what kinds of AIGC can become representative.

7. Findings / Analysis III: Cultural Legitimacy after Platform Mediation

This section addresses RQ3 by examining how algorithmic silence reshapes cultural legitimacy. The findings show that legitimacy is not a binary distinction between human and AI production. It is a relational process involving creators, texts, audiences, institutions, metrics, labels, and platform infrastructures.

Audience suspicion is one legitimacy filter. P01 did not reject AI as such. The participant distinguished between AI as a production tool and cultural works that feel detached from lived experience.

It is not AI itself that bothers me, but a kind of cultural collage without experience or lived feeling.

— P01, age 25, gender not disclosed, AIGC creator, Kuaishou

The empirical meaning is a judgment about cultural texture. The issue is not whether a work is produced with AI, but whether it carries context, experience, and situated intention. This distinction prevents the analysis from treating audiences as simply anti-AI.

Human-AI co-production is another legitimacy filter. Two creator accounts make visible the labor that one-click narratives tend to hide.

AI only produces the initial image; for it to become a work, humans still have to revise prompts, rhythm, and details repeatedly.

— P01, age 25, gender not disclosed, AIGC creator, Kuaishou

What audiences cannot see is that behind so-called one-click generation there is actually a great deal of judgment.

— P24, age 26, gender not disclosed, AIGC creator, Kuaishou

These accounts show that prompting, editing, selecting, revising, pacing, and cultural judgment remain part of production even when the interface presents generation as instant. The legitimacy problem is therefore double: audiences may distrust AIGC as too automated, while the human labor that could support legitimacy is itself weakly visible.

AI labels and disclosure practices further complicate legitimacy. Labels may increase trust by signaling transparency, but they can also trigger suspicion, stigma, or assumptions of lower effort. In the platform observation data, disclosure modes vary across explicit AI disclosure, platform label only, watermark, ambiguous disclosure, and no disclosure. A label is therefore not merely informational. It can position a work as honest, derivative, experimental, risky, or cheap depending on audience expectations and institutional context.

Metrics stabilize uncertain legitimacy into numbers. Metric proxy codes appear frequently in the dataset, and participants repeatedly describe views, completion rates, follower growth, and reposts as evidence used in collaboration and institutional recognition. This aligns with valuation theory: value is made through evaluative devices and social processes, not simply discovered [21,23,32]. Platform metrics become one such device.

At the same time, the data show resistance to metric legitimacy. P01's account of slow visibility separates weak immediate circulation from the absence of cultural value.

> *Slow visibility is not failure; it simply has not been recognized at the platform's speed.*
>
> — P01, age 25, gender not disclosed, AIGC creator, Kuaishou

RQ3 can therefore be answered as follows: algorithmic silence does not eliminate cultural legitimacy; it reorganizes legitimacy around visibility conditions that privilege measurable, recognizable, and institutionally low-risk forms. Other forms of value remain possible, but they require interpretive time, community memory, or institutional patience that platform metrics rarely capture.

8. Findings / Analysis IV: Methodological Silence and the Study of What Cannot Be Fully Seen

This section addresses RQ4. Methodological silence is not a secondary problem after analysis. It is one of the central conditions of studying platform-mediated invisibility. The empirical materials repeatedly show that personalized feeds, unstable search results, disappearing traces, screenshot limitations, and incomplete archives constrain what can be known. Table 3 summarizes the forms of silence and their methodological implications.

P04, a researcher/critic, described the basic problem of platform evidence: it can be real and still unstable.

> *Many platform traces can only be captured temporarily; after some time, they lose context.*
>
> — P04, age 35, male, researcher/critic, Douyin

A screenshot proves that a trace existed at a moment; it does not prove the full pathway through which the trace appeared, disappeared, or changed. This is why the analysis distinguishes trace evidence from algorithmic causality.

Personalization is another methodological problem. The same keyword, device, account, or timing condition may generate different results. The platform observation dataset partly responds to this by recording platform, post date, content type, AIGC method, disclosure mode, visibility score, stability index, and moderation/label status. Yet even this structure cannot fully reproduce the feed conditions under which a user encountered a work. The responsible analytical strategy is triangulation: combine platform traces with participant accounts, codebook logic, and literature while limiting causal claims.

Non-replicability does not make the study invalid. It changes the kind of validity that is appropriate. In algorithmic accountability research, external auditing often aims to infer system behavior through careful comparison [26]. This article's design is different. It examines how invisibility is experienced, coded, and methodologically constrained. The article therefore prioritizes credibility, transferability, reflexivity, and analytical adequacy rather than experimental control [8, 28, 33].

A second reflection from P04 captures the epistemic stakes without licensing speculation.

> *What cannot be seen is hard to prove, but precisely because it is hard to prove, it needs to be written about.*
>
> — P04, age 35, male, researcher/critic, Douyin

RQ4 can therefore be answered through method rather than certainty. Researchers can study platform-mediated invisibility responsibly when they document evidence boundaries, avoid overclaiming causal access, preserve traceability where possible, and protect participants and platform traces where necessary.

Table 3. Forms of Algorithmic Silence and Methodological Implications

Form of silence	Platform manifestation	Cultural effect	Methodological problem
Infrastructural silence	Weak recommendation, unstable search, ambiguous moderation.	Works exist but become hard to find, sustain, or explain.	Proprietary systems are inaccessible.
Metric silence	Low views, absent rankings, weak repostability.	Cultural value is discounted when it lacks measurable evidence.	Metrics cannot reveal interpretive depth.
Aesthetic silence	Template hooks, standardized visuals, accelerated storytelling.	Cultural nuance becomes decorative or compressed.	Aesthetic judgment is context-dependent.
Institutional silence	Preference for safe innovation and explainable AI effects.	Certain AIGC forms become representationally dominant.	Institutional decisions may not be publicly documented.
Methodological silence	Personalized feeds, screenshots without pathway data, disappearing links.	Invisible processes remain difficult to reproduce.	Causal proof is incomplete.
Slow visibility	Delayed recognition, saves, small communities, low immediate reach.	Cultural value may emerge outside platform acceleration.	Low metrics can mean many different things.

Note. Each form of silence creates both a cultural effect and a methodological constraint. The recommended strategies emphasize triangulation and causal restraint.

9. Discussion: Reversing the Assumption of Visibility

The findings reverse a common assumption in platform research: that visibility is primarily a measure of cultural success. In the case of AI-generated Chinese digital content, visibility is better understood as a governance condition. It organizes what can be discovered, counted, trusted, circulated, archived, and institutionally recognized. This does not mean that visibility is false or that metrics are useless. It means that visibility is socially and technically produced, and that its production must be analyzed before it can be used as evidence of cultural value. Table 4 summarizes how each research question is answered and what contribution follows from the answer.

Table 4. Research Questions, Analytical Answers, and Scholarly Contributions

RQ	Main answer	Data/evidence used	Contribution
RQ1	Visibility governs by organizing discoverability, metrics, interpretation, circulation, and recognition.	Creator/institutional interviews; trace variables; INF_RANK, MET_PROXY, CRE_SELF.	Reframes visibility as governance rather than exposure; shows how AIGC practice is shaped before circulation; links silence to weak legibility, not only deletion.
RQ2	Silence emerges through ranking opacity, moderation ambiguity, unstable search, metric proxy, aesthetic flattening, and selective recognition.	Coding matrix; theme map; moderation/label fields; selected excerpts.	Specifies mechanisms of quiet platform power; explains how AI content becomes standardized or institutionally filtered; develops a multidimensional model of silence.
RQ3	Legitimacy is reorganized through metrics, labels, authenticity judgments, institutional risk, and hidden human labor.	Audience, creator, and institutional accounts; AUD_AUTH, INST_LABEL, INST_BRAND, CO_PROD.	Connects platform metrics to legitimacy devices; moves beyond human-versus-AI binaries; shows how silence affects recognition without explicit prohibition.
RQ4	Researchers must study invisibility through triangulation, evidence hierarchy, and causal restraint.	METH_PERS, METH_TRACE, METH_CAUS; audit sheet.	Treats opacity as an empirical condition; offers a cautious method for platformed AIGC inquiry; makes methodological silence part of the intellectual contribution.

Note. The table maps each research question to its principal answer, evidence base, and contribution to platform, AIGC, and silence scholarship.

The article's first contribution is to platform studies. By conceptualizing algorithmic silence, it extends work on algorithmic power, platform governance, and creator visibility management [2, 9, 18, 31]. The concept identifies forms of governance that are quieter than deletion. Weak recommendation, unstable searchability, low metric legibility, template pressure, and institutional avoidance can all reduce cultural recognition without producing a clear moment of censorship. This matters because platform governance increasingly operates through ranking, recommendation, labeling, and monetization infrastructures rather than only through removal.

The second contribution is to AIGC studies. The analysis shows that AIGC legitimacy is not reducible to whether content is human or machine-made. Participants often cared less about AI as a tool than about whether AI-generated works carried experience, context, judgment, and cultural depth. Human-AI co-production appeared as a recurring theme: prompting, editing, selecting, revising, translating, and contextualizing remain forms of labor. Yet this labor can disappear behind the fantasy of one-click generation. Algorithmic silence therefore includes the invisibility of labor as well as the invisibility of content.

The third contribution is to cultural legitimacy theory. Legitimacy is usually studied through institutions, fields, categories, and audiences [6,23,32]. The present article shows that platform metrics and labels now operate as legitimacy devices. They do not replace traditional institutions, but they interact with them. Brands and cultural organizations may use views, completion rates, reposts, and AI labels to decide whether a work is innovative, risky, professional, or culturally valuable. Platform recognition and institutional recognition therefore become mutually reinforcing.

The fourth contribution is methodological. The article treats uncertainty as a condition of responsible platform research rather than a failure to be hidden. Personalized feeds, unstable searches, and disappearing traces require methods that can document partiality without overclaiming. The data structure used here—interview sample, coded excerpts, platform observations, coding matrix, theme-evidence map, and audit sheet—offers one model for such work. It does not solve opacity, but it makes analytical restraint visible. This is especially important for research on silence because the absent or weakly visible object can easily invite speculative explanation.

Slow visibility is the article's normative counter-concept. It does not claim that all slow or low-performing content is valuable. Rather, it names a mode of cultural recognition whose temporality differs from platform acceleration. Some cultural works require repeated viewing, community memory, local context, dialectal understanding, historical knowledge, or non-metric forms of care. Slow visibility asks researchers and institutions to separate cultural worth from immediate platform optimization. In this sense, it is not nostalgia for a pre-platform past. It is a forward-looking demand for evaluative systems that can recognize depth without requiring instant legibility.

The discussion also clarifies what the article does not claim. It does not claim that Chinese platforms uniquely produce silence, that AI-generated culture is inherently shallow, or that algorithmic governance is always suppressive. Nor does it claim access to proprietary ranking systems. Its claim is more precise: in platformized AIGC culture, visibility is a condition of governance, and silence often appears through weak legibility, metric absence, aesthetic standardization, institutional selectivity, and methodological incompleteness. This precision is what allows the concept to travel beyond the present case without losing empirical discipline.

10. Conclusion: Toward a Politics of Slow Visibility

This article has developed algorithmic silence as a concept for studying how platform visibility governs AI-generated Chinese digital content. Across the four research questions, the analysis has shown that visibility organizes the conditions under which AIGC works become discoverable, measurable, interpretable, circulatable, and institutionally recognizable; that silence is produced through ranking opacity, moderation ambiguity, unstable search, metric proxy, aesthetic flattening, selective recognition, and methodological uncertainty; that cultural legitimacy is reorganized through metrics, labels, audience judgment, institutional risk, and hidden human-AI labor; and that researchers must study invisibility through triangulation, evidence hierarchy, anonymization, and causal restraint.

The study's main limitation is that it cannot establish direct algorithmic causality. It analyzes anonymized interviews, coded excerpts, platform observation records, and audit materials, but it does not access internal recommendation systems or moderation rules. This is not a minor technical limitation; it is part of the condition the article conceptualizes as methodological silence. Future research could extend the framework through multi-account audits, longitudinal trace capture, cross-platform comparison, creator diary methods, institutional interviews, and ethically negotiated access to platform workers or policy teams where possible.

The politics of slow visibility begins from a refusal to collapse cultural value into platform speed. AI-generated cultural works may be visible and shallow, invisible and meaningful, technically impressive and culturally thin, or modest in circulation yet dense in context. A responsible theory of platform culture must hold these possibilities together while resisting the temptation to treat metrics as transparent evidence of worth. The article's central intervention is therefore not that platform governance always speaks through prohibition, but that it often governs by managing the conditions under which cultural works become visible, measurable, and recognizable. Algorithmic silence names this quieter politics of managed visibility: a form of governance that works through ranking, recommendation, metrics, labels, templates, institutional recognition, and methodological opacity. To write about silence is not to fill absence with certainty. It is to make the conditions of partial visibility available for careful, accountable interpretation.

Acknowledgments

The author thanks the interview participants and platform observers whose anonymized materials informed this study.

Conflict of Interest Statement

The author declares no conflict of interest.

Data Availability Statement

The anonymized interview excerpts, coding records, and platform observation materials analyzed in this article are not publicly available because they contain participant-sensitive contextual information and platform trace details. Selected anonymized excerpts and aggregated coding logic are reported in the manuscript.

Ethics Statement

Interview materials were anonymized before analysis. Participants were informed of the research purpose, and no personally identifiable information is reported. Platform observation materials are summarized or aggregated to avoid exposing account identities, direct URLs, or sensitive trace records.

References

[1] Ananny, M., & Crawford, K. (2018). Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability. *New Media & Society, 20*(3), 973–989. https://doi.org/10.1177/1461444816676645
[2] Beer, D. (2017). The social power of algorithms. *Information, Communication & Society, 20*(1), 1–13. https://doi.org/10.1080/1369118X.2016.1216147
[3] Bender, S. M. (2025). Generative-AI, the media industries, and the disappearance of human creative labour. *Media Practice and Education, 26*(2), 200–217. https://doi.org/10.1080/25741136.2024.2355597
[4] Bishop, S. (2019). Managing visibility on YouTube through algorithmic gossip. *New Media & Society, 21*(11–12), 2589–2606. https://doi.org/10.1177/1461444819854731
[5] Boden, M. A. (1998). Creativity and artificial intelligence. *Artificial Intelligence, 103*(1–2), 347–356. https://doi.org/10.1016/S0004-3702(98)00055-1
[6] Bourdieu, P. (1983). The field of cultural production, or: The economic world reversed. *Poetics, 12*(4–5), 311–356. https://doi.org/10.1016/0304-422X(83)90012-8
[7] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa
[8] Braun, V., & Clarke, V. (2019). Reflecting on reflexive thematic analysis. *Qualitative Research in Sport, Exercise and Health, 11*(4), 589–597. https://doi.org/10.1080/2159676X.2019.1628806
[9] Bucher, T. (2012). Want to be on the top? Algorithmic power and the threat of invisibility on Facebook. *New Media & Society, 14*(7), 1164–1180. https://doi.org/10.1177/1461444812440159
[10] Bucher, T. (2017). The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. *Information, Communication & Society, 20*(1), 30–44. https://doi.org/10.1080/1369118X.2016.1154086
[11] Burrell, J. (2016). How the machine "thinks": Understanding opacity in machine learning algorithms. *Big Data & Society, 3*(1), 1–12. https://doi.org/10.1177/2053951715622512
[12] Cotter, K. (2019). Playing the visibility game: How digital influencers and algorithms negotiate influence on Instagram. *New Media & Society, 21*(4), 895–913. https://doi.org/10.1177/1461444818815684
[13] Diakopoulos, N. (2015). Algorithmic accountability: Journalistic investigation of computational power structures. *Digital Journalism, 3*(3), 398–415. https://doi.org/10.1080/21670811.2014.976411
[14] Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642
[15] Floridi, L., & Chiriatti, M. (2020). GPT-3: Its nature, scope, limits, and consequences. *Minds and Machines, 30*(4), 681–694. https://doi.org/10.1007/s11023-020-09548-1
[16] Gillespie, T. (2010). The politics of platforms. *New Media & Society, 12*(3), 347–364. https://doi.org/10.1177/1461444809342738
[17] Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, P. J. Boczkowski, & K. A. Foot (Eds.), *Media technologies: Essays on communication, materiality, and society* (pp. 167–194). MIT Press. https://doi.org/10.7551/mitpress/9780262525374.003.0009
[18] Gorwa, R. (2019). What is platform governance? *Information, Communication & Society, 22*(6), 854–871. https://doi.org/10.1080/1369118X.2019.1573914
[19] Gorwa, R., Binns, R., & Katzenbach, C. (2020). Algorithmic content moderation: Technical and political challenges in the automation of platform governance. *Big Data & Society, 7*(1), 1–15. https://doi.org/10.1177/2053951719897945
[20] Helmond, A. (2015). The platformization of the web: Making web data platform ready. *Social Media + Society, 1*(2), 1–11. https://doi.org/10.1177/2056305115603080
[21] Johnson, C., Dowd, T. J., & Ridgeway, C. L. (2006). Legitimacy as a social process. *Annual Review of Sociology, 32*, 53–78. https://doi.org/10.1146/annurev.soc.32.061604.123101
[22] Kitchin, R. (2017). Thinking critically about and researching algorithms. *Information, Communication & Society, 20*(1), 14–29. https://doi.org/10.1080/1369118X.2016.1154087
[23] Lamont, M. (2012). Toward a comparative sociology of valuation and evaluation. *Annual Review of Sociology, 38*, 201–221. https://doi.org/10.1146/annurev-soc-070308-120022
[24] Liang, M., & Ye, L. (2025). Algorithmic pedagogy: How Douyin constructs algorithmic imaginaries for content creators. *Platforms & Society, 2*, 1–13. https://doi.org/10.1177/29768624251365615
[25] Meng, Z. (2026). Cross-platform sensitivity and algorithmic adaptability: How transnational creators navigate algorithms across Chinese and US-based platforms. *New Media & Society, 28*(3), 1171–1189. https://doi.org/10.1177/14614448241307578
[26] Metaxa, D., Park, J. S., Robertson, R. E., Karahalios, K., Wilson, C., Hancock, J., & Sandvig, C. (2021). Auditing algorithms. *Foundations and Trends in Human–Computer Interaction, 14*(4), 272–344. https://doi.org/10.1561/1100000083

[27] Nieborg, D. B., & Poell, T. (2018). The platformization of cultural production: Theorizing the contingent cultural commodity. *New Media & Society, 20*(11), 4275–4292. https://doi.org/10.1177/1461444818769694
[28] Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International Journal of Qualitative Methods, 16*(1), 1–13. https://doi.org/10.1177/1609406917733847
[29] Poell, T., Nieborg, D., & van Dijck, J. (2019). Platformisation. *Internet Policy Review, 8*(4), 1–13. https://doi.org/10.14763/2019.4.1425
[30] Rieder, B., Matamoros-Fernández, A., & Coromina, Ò. (2018). From ranking algorithms to "ranking cultures": Investigating the modulation of visibility in YouTube search results. *Convergence, 24*(1), 50–68. https://doi.org/10.1177/1354856517736982
[31] Seaver, N. (2017). Algorithms as culture: Some tactics for the ethnography of algorithmic systems. *Big Data & Society, 4*(2), 1–12. https://doi.org/10.1177/2053951717738104
[32] Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of Management Review, 20*(3), 571–610. https://doi.org/10.5465/amr.1995.9508080331
[33] Tracy, S. J. (2010). Qualitative quality: Eight "big-tent" criteria for excellent qualitative research. *Qualitative Inquiry, 16*(10), 837–851. https://doi.org/10.1177/1077800410383121
[34] van Dijck, J., & Poell, T. (2013). Understanding social media logic. *Media and Communication, 1*(1), 2–14. https://doi.org/10.17645/mac.v1i1.70
[35] Yang, Y., & Ha, L. (2021). Why people use TikTok (Douyin) and how their purchase intentions are affected by social media influencers in China: A uses and gratifications and parasocial relationship perspective. *Journal of Interactive Advertising, 21*(3), 297–305. https://doi.org/10.1080/15252019.2021.1995544
[36] Ye, Z., Huang, Q., & Krijnen, T. (2025). Douyin's playful platform governance: Platform's self-regulation and content creators' participatory surveillance. *International Journal of Cultural Studies, 28*(1), 80–98. https://doi.org/10.1177/13678779241247065
[37] Zhang, L., & Chen, J. Y. (2022). A regional and historical approach to platform capitalism: The cases of Alibaba and Tencent. *Media, Culture & Society, 44*(8), 1454–1472. https://doi.org/10.1177/01634437221127796