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WHEN MACHINES BECOME THE AUDIENCE: RETHINKING COMMUNICATION THEORY IN THE AGE OF GENERATIVE AI

A CONCEPTUAL MODEL OF ALGORITHMIC COMMUNICATION READINESS

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ABSTRACT

Generative artificial intelligence alters a long-standing assumption in communication theory: that a human receiver encounters the message that a communicator releases. Today, computational systems often retrieve, rank, combine, and rewrite public information before a person sees it. This article develops Algorithmic Communication Readiness (ACR), defined as the capacity of a communicator's public digital record to support accurate, consistent, and well-evidenced machine interpretation while preserving meaning for people. The study uses an integrative conceptual review and theory-building process informed by human-machine communication, AI-mediated communication, machine agency, gatekeeping, media ecology, signalling, source credibility, and affordance theory. The review identifies four constitutive dimensions of ACR: semantic clarity, identity consistency, evidential density, and cross-platform coherence. Machine-human interpretive alignment is repositioned as the model's immediate outcome rather than as a fifth dimension. The model also introduces machine interpretive noise to describe omission, distortion, decontextualization, and unsupported synthesis in AI-generated accounts. Six propositions explain how ACR may shape alignment and, in turn, influence perceived accuracy and credibility. The article contributes a communication-centred account of the public digital record as material that is increasingly read by both people and computational systems. It concludes with implications for journalism, public relations, public institutions, science communication, and media literacy, and outlines a programme for scale development, experiments, longitudinal audits, and cross-language research.

Keywords: Algorithmic Communication Readiness, Generative AI, Human-Machine Communication, Digital Media, Algorithmic Gatekeeping, Source Credibility

INTRODUCTION

Communication research has usually located technology between people. A medium carries a message, a platform distributes it, and an audience interprets it. Generative artificial intelligence (AI) changes this sequence. A computational system may now encounter the public record first, select material from it, combine several sources, and produce the version that a person reads. The human receiver may therefore respond to a generated account rather than to the original message.

This change builds on two earlier developments. First, platforms and search systems became powerful selectors of visibility and relevance Beer (2017), Gillespie (2014), Napoli (2019). Second, communication scholars began to treat machines as communicative

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agents rather than as neutral channels Guzman and Lewis (2020), Sundar (2020). AI-mediated communication research further shows that computational agents can modify, augment, or generate messages on behalf of communicators Hancock et al. (2020). Generative systems add another role: they can read a distributed set of public messages and assemble a new account for a user.

Existing scholarship explains important parts of this development but leaves a practical and theoretical gap. Human-machine communication asks how people communicate with machines and how machines acquire communicative roles. Algorithmic gatekeeping explains how systems select and rank information. Platform studies explain how infrastructures shape public visibility. These traditions do not yet provide a clear construct for assessing whether a communicator's public digital record is prepared for computational interpretation. The question is no longer only whether information can be found. It is also whether a machine-produced account preserves identity, context, evidence, and the limits of a claim.

This article introduces Algorithmic Communication Readiness (ACR) to address that gap. ACR is the capacity of a communicator's public digital record to support accurate, consistent, and well-evidenced machine interpretation while remaining meaningful to people. The phrase "machines become the audience" is used functionally, not literally. Computational systems do not become social audiences with consciousness or shared identity. They occupy an audience-like position because they receive and process communication before many human encounters.

The article makes four contributions. It distinguishes machine interpretation from both transmission and distribution. It defines ACR through four dimensions rather than treating machine visibility as readiness. It introduces machine interpretive noise as a communication problem created during computational synthesis. Finally, it links readiness to machine-human interpretive alignment and offers propositions that can be tested across systems, languages, and communication settings.

LITERATURE AND THEORETICAL FOUNDATIONS

HUMAN-MACHINE AND AI-MEDIATED COMMUNICATION

Human-machine communication (HMC) challenges the idea that machines are only conduits. Guzman and Lewis (2020) show why AI technologies require communication research to consider machines as communicative subjects and objects. Sundar (2020) develops the related idea of machine agency and examines how users respond when technologies appear to act with autonomy. More recent work connects HMC with explainable AI and argues that message production, system explanation, and human oversight should be examined together Xu and Shi (2024). A systematic review of HMC research also shows a shift from robots toward virtual agents, chatbots, and generative AI, while noting increasing overlap between HMC and AI-mediated communication Liu et al. (2026).

AI-mediated communication takes a different but complementary view. Hancock et al. (2020) define it as interpersonal communication in which an intelligent agent modifies, augments, or generates messages to achieve communication goals. That definition starts with an agent acting for a communicator. ACR starts at another point: a system interprets communication that already exists across a public digital record. The two perspectives meet when generated outputs shape how people understand a source.

GATEKEEPING, PLATFORM POWER, AND GENERATIVE SYNTHESIS

Gatekeeping theory asks how information passes through selection points. In digital environments, algorithms help determine which messages become visible and relevant Gillespie (2014). Their influence is social as well as technical because classification, ranking, and recommendation shape what users can encounter Beer (2017). Napoli (2019) extends this concern to social media and the public interest, where platforms perform functions once associated with media institutions.

Generative AI adds synthesis to selection. A system can create a compact answer from several sources, remove qualifiers, merge different time periods, or attach a claim to the wrong entity. Voinea (2025) argues that AI-driven curation and automated journalism require a hybrid account of gatekeeping. Critical work on algorithmic mediation similarly treats algorithms as participants in the production and circulation of meaning rather than as neutral delivery tools Sánchez-Vera (2025). ACR builds on this literature by placing the quality of the underlying public record inside the gatekeeping problem.

MEDIA ECOLOGY AND MEDIATIZATION

Media ecology and mediatization help explain why a new medium changes more than message delivery. Media environments shape the conditions under which institutions, practices, and meanings are organized Couldry and Hepp (2017), McLuhan (1964). Generative systems create an environment in which communication is repeatedly converted into data, retrieved fragments, and synthesized responses. From this perspective, ACR is not a writing technique. It is a property of the distributed record through which communicators become knowable in an AI-shaped media environment.

SIGNALLING AND SOURCE CREDIBILITY

Signalling theory explains how observers infer qualities that are not directly visible from available signals Spence (1973). Source-credibility research shows that trustworthiness and expertise affect how messages are judged Hovland and Weiss (1951). These traditions give "evidential density" its theoretical basis. A repeated claim is not necessarily a strong signal. A stronger record links the claim to specific facts, primary documents, stable attribution, and credible corroboration. Recent research on AI-mediated communication also warns that generative systems can complicate epistemic trust, because users may have difficulty deciding when lower trust is justified Sahebi and Formosa (2025).

AFFORDANCES AND SOCIOTECHNICAL CONDITIONS

Affordance theory directs attention to what technologies enable or constrain in relation to users and goals Evans et al. (2017). Generative systems afford rapid retrieval and synthesis, but these capacities vary by architecture, source access, language, query, and recency. Sociotechnical approaches add that outputs arise from relations among systems, data, institutions, policies, and users rather than from one algorithm acting alone Latour (2005). ACR therefore cannot guarantee a correct output. It identifies communication conditions that may improve the prospects of faithful interpretation within a variable system environment.

METHOD: INTEGRATIVE CONCEPTUAL REVIEW AND THEORY DEVELOPMENT

The study used an integrative conceptual review because the research problem spans communication theory, platform studies, human-machine communication, and AI research. Integrative reviews are suited to topics that require the combination of established and emerging bodies of knowledge, while conceptual articles are expected to clarify constructs, explain relationships, and provide a coherent basis for future testing Jaakkola (2020), Snyder (2019), Torraco (2005). The aim was not to estimate an effect or claim exhaustive coverage. It was to build and delimit a construct that addresses a communication problem not fully captured by existing concepts.

REVIEW SCOPE AND SOURCE IDENTIFICATION

The review was organized around six literature clusters: classical communication models; HMC and AI-mediated communication; machine agency; algorithmic gatekeeping and platform power; signalling and source credibility; and media ecology, affordances, and sociotechnical theory. Search phrases combined terms such as "human-machine communication," "AI-mediated communication," "machine agency," "algorithmic gatekeeping," "generative AI communication," "source credibility," "algorithmic mediation," and "explainable AI communication." Foundational works were retained when they supplied concepts required to define the model; recent peer-reviewed work was used to address generative systems and contemporary communication practices.

SELECTION AND ANALYTICAL LOGIC

Sources were included when they met at least one of three criteria: they explained the role of machines or platforms in communication; they supplied a theory for one of the proposed dimensions; or they helped distinguish ACR from an adjacent construct. Sources concerned only with technical model performance were not used unless they directly informed the communication problem. The analysis then proceeded through five steps: mapping the role assigned to technology in each literature; identifying what changes when systems synthesize rather than merely transmit or rank; extracting recurring requirements for faithful interpretation; grouping those requirements into distinct dimensions; and deriving propositions that connect the dimensions to an observable outcome.

CONSTRUCT DEVELOPMENT

The initial conceptualization treated machine-human interpretive alignment as one of five ACR dimensions. Closer analysis revealed a circularity: alignment was both part of readiness and the result readiness was expected to produce. The revised model therefore defines ACR through four constitutive dimensions: semantic clarity, identity consistency, evidential density, and cross-platform coherence. Machine-human interpretive alignment is treated as the immediate outcome. This gives the construct a cleaner causal order and makes empirical testing more direct.

The review followed concept-centric synthesis rather than author-by-author summary Webster and Watson (2002). Each proposed dimension was required to meet three tests: conceptual distinctiveness, relevance to machine interpretation, and potential observability in public communication. The resulting framework remains provisional. Its value depends on later scale development, content coding, experiments, and audits of generated outputs.

DEFINING ALGORITHMIC COMMUNICATION READINESS

Algorithmic Communication Readiness is the capacity of a communicator's public digital record to support accurate, consistent, and well-evidenced machine interpretation while preserving meaning for people. The unit of concern is the public digital record, not one message. That record may include websites, reports, public databases, news coverage, professional profiles, social posts, metadata, and third-party references.

ACR is a formative construct. Its four dimensions contribute different qualities, and weakness in one cannot be assumed to disappear because another is strong. Clear language cannot resolve a mistaken identity. A consistent identity cannot make an unsupported claim credible. Strong evidence may still be difficult to connect if platforms present incompatible descriptions. This formative specification should be tested empirically rather than accepted solely on conceptual grounds.

SEMANTIC CLARITY

Semantic clarity is the extent to which public communication names subjects, relationships, claims, and limits explicitly enough to reduce avoidable ambiguity. It does not mean writing for keywords or stripping away nuance. It means giving both people and systems enough context to determine who or what a statement concerns, what is being claimed, and under what conditions the claim applies.

Proposition 1. Greater semantic clarity will be associated with more consistent identification of the communicator's subject and principal claims in AI-generated accounts.

IDENTITY CONSISTENCY

Identity consistency is the compatibility of names, roles, affiliations, and entity relationships across public sources. The same organization may appear under several abbreviations, while a person's role may differ across profiles and older documents. Such variation can be legitimate, but unexplained conflict increases the risk of mistaken attribution.

Proposition 2. Greater identity consistency across public sources will be associated with fewer attribution errors in AI-generated accounts.

EVIDENTIAL DENSITY

Evidential density is the presence of specific, credible, and verifiable support around important claims. Density refers to the relationship between claim and evidence, not to the volume of repeated content. Useful evidence may include primary documents, dates, named programmes, transparent methods, correction histories, and credible third-party confirmation.

Proposition 3. Greater evidential density will be associated with a higher proportion of source-supported claims in AI-generated accounts.

CROSS-PLATFORM COHERENCE

Cross-platform coherence is the extent to which core facts and context remain compatible across formats and channels. Coherence does not require identical wording. A news release, annual report, biography, and social post serve different purposes. The issue is whether the underlying identity, dates, claims, and relationships remain materially consistent.

Proposition 4. Greater cross-platform coherence will be associated with fewer contradictions in AI-generated accounts of the communicator.

MACHINE-HUMAN INTERPRETIVE ALIGNMENT AND MACHINE INTERPRETIVE NOISE

Machine-human interpretive alignment is the degree to which an AI-generated account preserves the communicator's intended identity, context, evidence, and claim boundaries in a form that a human audience can reasonably understand. Alignment is not perfect agreement with the communicator, nor does it give the communicator control over criticism. It asks whether the generated account represents the available record fairly and accurately.

Machine interpretive noise refers to distortion introduced during computational retrieval and synthesis. Four forms are especially relevant: omission of material context; distortion of a claim or relationship; decontextualization across time, source, or setting; and unsupported synthesis that presents a plausible statement without adequate evidence. Hallucination is one possible form, but the concept is broader because a statement can be factually plausible and still misrepresent context.

Proposition 5. Higher ACR will be associated with stronger machine-human interpretive alignment, after accounting for system conditions such as source access, language, query, model architecture, and recency.

Proposition 6. Stronger machine-human interpretive alignment will be associated with higher perceived accuracy and source credibility among human audiences, conditional on prior attitudes, disclosure, task, and system used.

CONCEPTUAL MODEL

Figure 1 places ACR within a wider communication sequence. A communicator contributes to a public digital record. A machine interpretive layer retrieves and processes parts of that record under system-specific conditions. The system produces a generated account, which may contain interpretive noise. Human audiences then evaluate that account, and their behaviour can add new data to the public record. The model assigns ACR to the record before machine processing and treats alignment as the first outcome after generation. This separation avoids presenting alignment as both a cause and an effect.

Figure 1

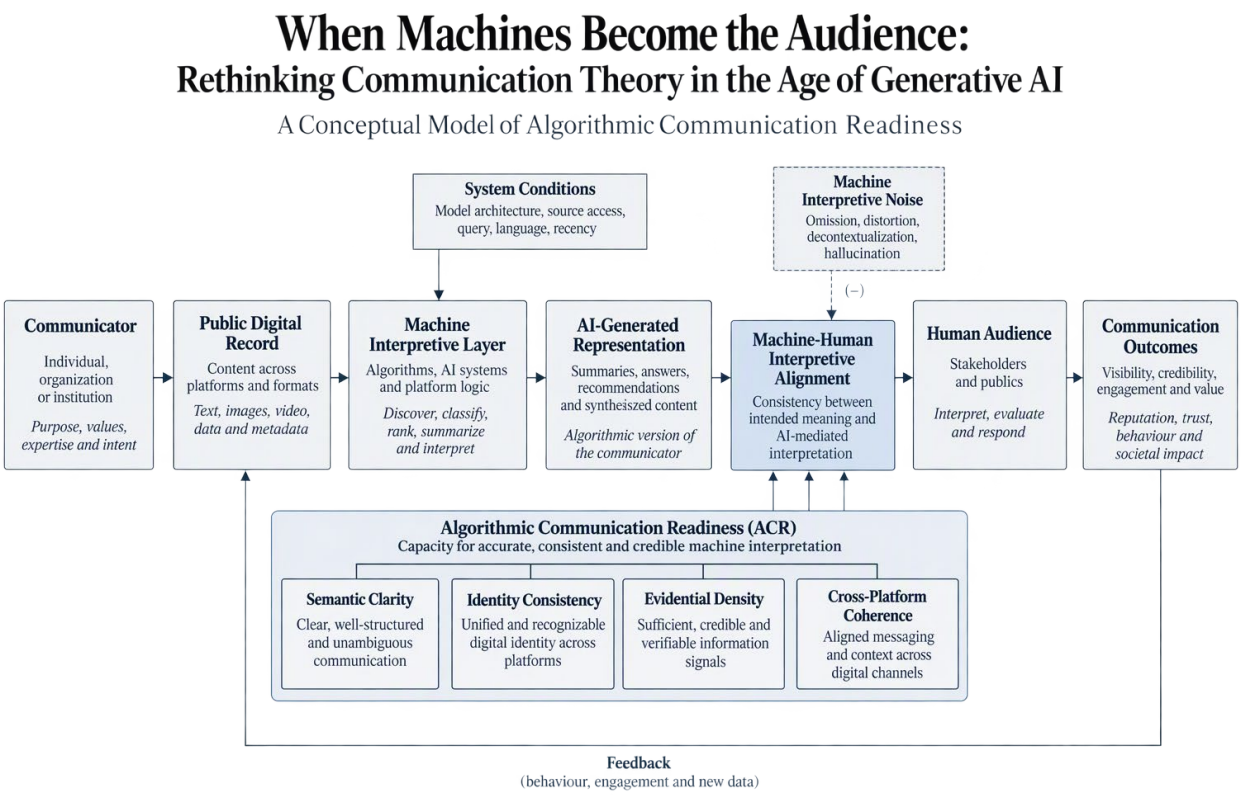


Figure 1 Algorithmic Communication Readiness Model

Note Solid Arrows Show Proposed Relationships. The Dashed Path Represents Possible Interpretive Noise. The Model is Conceptual and Does not Establish Causal Effects. Visual on this Slide was Generated with Microsoft Copilot

DISCUSSION

THEORETICAL REFRAMING: FROM MESSAGE DELIVERY TO PUBLIC-RECORD READINESS

The model changes the object of analysis. Traditional models often begin with a message. ACR begins with a public record made up of many messages, formats, and sources. This shift reflects how generative systems often work: they do not simply receive one bounded text but assemble an answer from available traces. Communication quality therefore includes the relation among those traces, not only the quality of each item.

This reframing also clarifies the paper's place within HMC. HMC studies machines as communicative agents and explores how people understand and relate to them Guzman and Lewis (2020), Liu et al. (2026). ACR asks how other communicators become legible through those agents. It is therefore not a replacement for HMC but an upstream construct within an AI-shaped communication process.

EXTENDING GATEKEEPING FROM SELECTION TO SYNTHESIS

Algorithmic gatekeeping explains why some information becomes visible and other information recedes. ACR adds a second question: what happens after selection? A generated answer can preserve, compress, alter, or invent relationships among selected fragments. The move from selection to synthesis increases the importance of context, entity stability, and evidence. It also complicates accountability because the resulting account may reflect source material, model design, retrieval choices, and user prompts at the same time.

This extension should not be read as technological determinism. Couldry and Hepp (2017) show that mediated reality is produced through social and institutional processes, while affordance approaches emphasize relations among technology, users, and aims Evans et al. (2017). The same public record can yield different accounts across systems or queries. ACR improves the input conditions; it does not control the outcome.

CREDIBILITY WITHOUT OPTIMIZATION

The distinction between readiness and optimization is normatively important. If communicators pursue only visibility, they may flood platforms with repetitive, simplified, or strategically engineered content. Such practices can weaken public knowledge even if they improve retrieval. By grounding ACR in signalling and source credibility, the framework treats evidence and faithful attribution as central. A communication record is ready not when it attracts a system's attention, but when it helps the system distinguish what is known, who is responsible, and where uncertainty remains.

CONTRIBUTION TO COMMUNICATION THEORY

The paper contributes to communication theory in four ways. First, it identifies a machine interpretive layer that sits between public communication and many human encounters. Second, it moves analysis from the single message to the distributed public record. Third, it separates four antecedent qualities from the immediate outcome of interpretive alignment. Fourth, it updates the idea of noise for a setting in which distortion may be produced through synthesis rather than transmission failure.

The contribution is deliberately limited. ACR does not claim that communication alone determines AI output, that systems understand meaning as people do, or that communicators should tailor all speech to machines. The framework instead offers a way to study how message design, identity management, evidence, and cross-platform consistency interact with system conditions to shape generated accounts.

PRACTICAL IMPLICATIONS

For journalism, the model draws attention to attribution, corrections, durable links, dates, and the distinction between fact and opinion. For public relations and corporate communication, it encourages consistent names, roles, programme descriptions, and evidence across public sources. For public institutions and science communication, it highlights the danger of losing qualifiers when complex material is compressed. For media literacy, it reinforces the need to treat generated answers as constructed accounts that should be checked against original sources.

BOUNDARY CONDITIONS AND ETHICAL RISKS

ACR is constrained by system architecture, source access, indexing, retrieval design, language, model updates, query wording, and time. Information behind access controls may not be available. Older material may outweigh corrections. Minority languages and transliterated names may create additional ambiguity. Political pressure, coordinated misinformation, impersonation, and content farms can also overwhelm a careful public record. These conditions should be measured rather than treated as residual error.

Ethically, ACR must not become a licence for manipulating AI systems or crowding out less resourced voices. Organizations with larger communication budgets may create denser digital records than smaller institutions, regardless of the quality of their claims. A readiness framework must therefore remain tied to evidence, correction, plural sources, and public accountability. Critical algorithmic mediation reminds researchers that systems operate within unequal structures of visibility and authority Sánchez-Vera (2025).

RESEARCH AGENDA

Construct validation should begin with expert interviews and a structured content-coding study across organizational and public communication records. Researchers can generate candidate indicators for each dimension, assess content validity, and test whether

the dimensions behave formatively. Measures of alignment should be developed separately through blinded human comparison of source records and AI-generated accounts.

Experiments can manipulate one dimension at a time. For example, researchers could vary role names across platforms to test attribution, add or remove primary evidence to test source support, or alter contextual qualifiers to test omission. Outputs should be compared across systems, prompts, languages, and dates. The unit of analysis must be archived carefully because generated outputs can change.

Longitudinal audits could examine whether corrections to a public record are followed by changes in generated accounts. Cross-language studies should test transliteration, translation, and culturally specific names. Comparative research across journalism, government, healthcare, higher education, business, and civil society can reveal whether evidential expectations differ by field. Research should also examine unequal readiness, including whether smaller or less digitized organizations are systematically misrepresented.

LIMITATIONS

This is a conceptual study. The proposed dimensions, formative specification, and propositions have not been validated. The review is integrative rather than systematic and does not claim exhaustive coverage of a fast-changing field. The model simplifies technical systems that differ in training, retrieval, source access, and output design. It also uses "audience" as a functional metaphor; it does not attribute consciousness, social membership, or human understanding to computational systems. Finally, strong ACR cannot overcome every limitation of an AI system or every conflict in the public record.

CONCLUSION

Generative AI changes how public communication reaches people. A system may encounter the public record first, select parts of it, and create the version that a person reads. Communication theory therefore needs a way to study not only messages and channels but also whether a distributed record can withstand computational interpretation.

Algorithmic Communication Readiness provides that lens. Semantic clarity, identity consistency, evidential density, and cross-platform coherence describe the conditions of a prepared public record. Machine-human interpretive alignment describes the immediate outcome, while machine interpretive noise captures the ways synthesis can go wrong. The framework does not ask communicators to write for machines instead of people. It asks them to build a public record that is clear, accountable, and useful when communication is read by both.

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REFERENCES

Beer, D. (2017). The Social Power of Algorithms. Information, Communication & Society, 20(1), 1–13. https://doi.org/10.1080/1369118X.2016.1216147

Couldry, N., and Hepp, A. (2017). The Mediated Construction of Reality. Polity Press.

Evans, S. K., Pearce, K. E., Vitak, J., and Treem, J. W. (2017). Explication of Affordances: A Conceptual Framework for Understanding Affordances in Communication Research. Journal of Computer-Mediated Communication, 22(1), 35–52. https://doi.org/10.1111/jcc4.12180

Gillespie, T. (2014). The Relevance of Algorithms. In T. Gillespie, P. J. Boczkowski, and K. A. Foot (Eds.), Media Technologies: Essays on Communication, Materiality, and Society (167–194). MIT Press.

Guzman, A. L., and Lewis, S. C. (2020). Artificial Intelligence and Communication: A Human–Machine Communication Research Agenda. New Media & Society, 22(1), 70–86. https://doi.org/10.1177/1461444819858691

Hancock, J. T., Naaman, M., and Levy, K. (2020). Ai-Mediated Communication: Definition, Research Agenda, and Ethical Considerations. Journal of Computer-Mediated Communication, 25(1), 89–100. https://doi.org/10.1093/jcmc/zmz022

Hovland, C. I., and Weiss, W. (1951). The Influence of Source Credibility on Communication Effectiveness. Public Opinion Quarterly, 15(4), 635–650. https://doi.org/10.1086/266350

Jaakkola, E. (2020). Designing Conceptual Articles: Four Approaches. AMS Review, 10, 18–26. https://doi.org/10.1007/s13162-020-00161-0

Latour, B. (2005). Reassembling the Social: An Introduction to Actor-Network-Theory. Oxford University Press.

Liu, F., Chen, X., and Xu, K. (2026). Charting the Evolution of Human–Machine Communication: A Systematic Review of 25 Years of Empirical Research. Annals of the International Communication Association, 1–21. https://doi.org/10.1093/anncom/wlag033

McLuhan, M. (1964). Understanding Media: The Extensions of Man. McGraw-Hill.
Napoli, P. M. (2019). Social Media and the Public Interest: Media Regulation in the Disinformation Age. Columbia University Press.
Sahebi, S., and Formosa, P. (2025). The AI-Mediated Communication Dilemma: Epistemic Trust, Social Media, and the Challenge of Generative Artificial Intelligence. Synthese, 205. https://doi.org/10.1007/s11229-025-04963-2
Shannon, C. E., and Weaver, W. (1949). The Mathematical Theory of Communication. University of Illinois Press.
Snyder, H. (2019). Literature Review as a Research Methodology: An Overview and Guidelines. Journal of Business Research, 104, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039
Spence, M. (1973). Job Market Signaling. The Quarterly Journal of Economics, 87(3), 355–374. https://doi.org/10.2307/1882010
Sundar, S. S. (2020). Rise of Machine Agency: A Framework for Studying the Psychology of Human–AI Interaction. Journal of Computer-Mediated Communication, 25(1), 74–88. https://doi.org/10.1093/jcmc/zmz026
Sánchez-Vera, F. (2025). Critical Algorithmic Mediation: Rethinking Cultural Transmission and Education in the Age of Artificial Intelligence. Societies, 15(7), Article 198. https://doi.org/10.3390/soc15070198
Torraco, R. J. (2005). Writing Integrative Literature Reviews: Guidelines and Examples. Human Resource Development Review, 4(3), 356–367. https://doi.org/10.1177/1534484305278283
Voinea, D. V. (2025). Reconceptualizing Gatekeeping in the Age of Artificial Intelligence: A Theoretical Exploration of Artificial Intelligence-driven News Curation and Automated Journalism. Journalism and Media, 6(2), Article 68. https://doi.org/10.3390/journalmedia6020068
Webster, J., and Watson, R. T. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. MIS Quarterly, 26(2), xiii–xxiii.
Xu, K., and Shi, J. (2024). Visioning a Two-Level Human–Machine Communication Framework: Initiating Conversations between Explainable AI and Communication. Communication Theory, 34(4), 216–229. https://doi.org/10.1093/ct/qtae016