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AI Literacy as Science Communication: Building Public Understanding through Pedagogical Innovation

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Abstract: As artificial intelligence (AI) systems become embedded in everyday communication, education, and decision-making, public AI literacy has become a pressing science communication challenge. This paper reconceptualizes AI literacy as a science communication task rather than a narrowly technical educational objective. Using a scoping-review-informed synthesis of interdisciplinary literature, the manuscript integrates scholarship from AI literacy, science communication, informal learning, and educational technology to derive the COMMUNICATE framework. The review drew on iterative searches of Google Scholar, Scopus-indexed sources available to the author, and backward reference tracing. Sources were included when they addressed AI literacy frameworks, public engagement and science communication theory, or empirical findings relevant to pedagogy, trust, participation, and AI-supported learning design. The resulting framework organizes eleven principles: Contextualized understanding, Open dialogue, Multimodal representation, Meaning-making, Universal accessibility, Narrative engagement, Interactive exploration, Critical evaluation, Adaptive scaffolding, Transformative learning, and Ethical reflection. The paper argues that a science communication perspective adds value by foregrounding audience diversity, public trust, dialogic participation, and interpretive context, which are often underdeveloped in technically oriented AI literacy models. The manuscript concludes by outlining practical implications for educators, communicators, and policymakers, while explicitly acknowledging the framework's conceptual status and the need for future empirical validation across formal and informal settings.

Keywords: AI Literacy; Science Communication; Public Understanding of Science; Pedagogical Innovation; Generative AI; Visualization; Public Engagement

1. Introduction

The rapid proliferation of artificial intelligence (AI) technologies, particularly generative AI systems such as ChatGPT, DALL-E, and similar tools, has fundamentally transformed how individuals interact with technology in their daily lives [1]. Since late 2022, generative AI has transitioned from specialized technical domains to mainstream public accessibility, raising urgent questions about how to effectively communicate complex AI concepts to diverse publics. This technological democratization presents unprecedented challenges and opportunities for science communication, as the public must navigate an increasingly AI-mediated information landscape.

Science communication has historically served as the bridge between specialized scientific knowledge and public understanding, employing strategies ranging from visualization to narrative engagement to make complex concepts accessible. AI presents unique challenges for science communicators: its underlying mechanisms are often opaque ("black box" algorithms), its capabilities are rapidly evolving, and its societal implications span ethical, economic, and existential dimensions. Moreover, AI itself has become both an object of science communication—requiring explanation—and an agent of science communication—generating content, personalizing information, and mediating public engagement with scientific topics.

AI literacy, defined as "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace" [2], has emerged as a crucial educational objective. However, AI literacy education has primarily been conceptualized within computer science and educational technology frameworks, with insufficient attention to its role as a form of science communication aimed at building public understanding.

This paper advances the argument that AI literacy education should be reconceptualized as science communication, leveraging established principles from the public understanding of science (PUS) field to develop more effective pedagogical approaches. We propose that pedagogical innovation—encompassing visualization strategies, interactive learning tools, and multimodal communication approaches—represents the primary mechanism through which public AI literacy can be achieved at scale. By synthesizing research from AI literacy, science communication, and educational technology, this paper offers a comprehensive framework for understanding how AI knowledge can be effectively communicated to diverse publics.

This revised version makes three clarifications that are central to the paper's contribution. First, the manuscript is framed as a scoping-review-informed conceptual synthesis rather than as a systematic review, because its primary aim is to integrate strands of literature and derive a usable framework for practice. Second, the science communication perspective is treated as essential, not decorative: it shifts AI literacy from a narrow concern with technical competence to a broader concern with audience, trust, participation, interpretation, and public decision-making. Third, the COMMUNICATE model is presented as a framework to be tested and refined, not as a fully validated endpoint.

Review Scope, Source Selection, and Framework Derivation

To improve methodological transparency, this paper now specifies how the literature base was assembled. The review followed a scoping logic appropriate for an emerging, interdisciplinary field in which concepts, theories, and pedagogical models are distributed across education, communication, and sociotechnical research. Searches were conducted iteratively across Google Scholar, Scopus-indexed journal databases available to the author, and reference lists of major review papers using combinations of terms such as "AI literacy," "artificial intelligence education," "science communication," "public understanding of science," "dialogue model," "informal science learning," "trust in AI," and "generative AI education."

The initial pool prioritized literature published between 2020 and 2024 because of the acceleration of generative AI adoption, but foundational works before 2020 were deliberately added when they shaped the field's conceptual vocabulary or policy direction, including Touretzky et al. [3], Kandlhofer et al. [4], and core science communication scholarship by Bucchi and Trench [5], Davies et al. [6], and Nisbet and Scheufele [7]. Recent studies published after 2024 were also incorporated when they clarified emerging empirical trends or implementation challenges, including work on learning analytics and pedagogical perspectives in generative AI. Sources were retained when they met at least one of three criteria: they proposed or reviewed AI literacy frameworks, they contributed science communication theory relevant to public understanding and engagement, or they reported empirical findings on pedagogy, trust, public participation, or AI-supported learning design.

Sources were excluded when they were purely technical, focused only on algorithmic performance without educational or communicative implications, or discussed AI in education without relevance to literacy, public understanding, or pedagogy. Framework derivation proceeded through qualitative synthesis: recurrent design principles were identified across the retained literature, compared against science communication theory and learning theory, and then clustered into the eleven elements of COMMUNICATE. Accordingly, the manuscript should be read as a traceable conceptual framework built from a transparent review process, while also acknowledging that formal empirical validation remains future work.

2. Theoretical Foundations

2.1. AI Literacy: Conceptualization and Frameworks

The conceptualization of AI literacy has evolved significantly over the past five years, moving from a niche subfield of computer science education to a multidisciplinary imperative. Long and Magerko provided the foundational framework, identifying 17 core competencies organized around five thematic questions: What is AI? What can AI do? How does AI work? How should AI be used? How do people perceive AI? [2] This framework was pivotal because it emphasized that AI literacy extends beyond technical knowledge—such as coding or understanding neural architecture—to encompass critical evaluation, ethical reasoning, and practical application skills. For instance, competencies include "recognizing AI" in everyday environments and "understanding that AI systems learn from data," which are essential precursors to identifying bias or algorithmic error.

Ng et al. further elaborated on AI literacy, proposing four cognitive domains: (1) know and understand AI, (2) use and apply AI, (3) evaluate and create AI, and (4) AI ethics [8]. This framework, grounded in Bloom's taxonomy, provided a hierarchical structure for curriculum development and assessment, suggesting a progression from lower-order thinking (recall and basic usage) to higher-order thinking (creation and ethical critique). Importantly, Ng et al. emphasized that AI literacy should not be limited to technical specialists but should be accessible to all citizens navigating an AI-permeated society. This implies that the goal of literacy is not necessarily to create more engineers, but to create "informed critics" and "competent users" who can leverage AI tools while understanding their limitations.

More recently, frameworks have expanded to include "AI competency," distinguishing between literacy (knowing what skills) and competency (applying knowledge with confidence in complex, real-world situations). The UNESCO AI Competency Framework for Teachers and related student guidance further institutionalized these concepts, outlining competencies across dimensions such as human-centered mindset, ethics of AI, and AI pedagogy [9]. This institutional shift signals a recognition that AI literacy is now a foundational transversal skill comparable to reading or numeracy, required not just for employment but for civic participation.

Systematic reviews by Almatrafi et al. and Casal-Otero et al. reveal that while technical understanding remains important, ethical and societal dimensions have gained increasing prominence [10,11]. This reflects a shift from a skills-based approach to a citizenship-based approach, aligning closely with the goals of modern science communication. In this expanded view, a literate citizen is one who can debate the fairness of facial recognition surveillance or the copyright implications of generative art, rather than merely one who can optimize a prompt.

Two foundational works that strengthen this genealogy deserve explicit acknowledgment. Touretzky et al. articulated the AI4K12 perspective that every learner should understand perception, representation and reasoning, learning, human-AI interaction, and societal impact [3]. Kandlhofer et al. likewise argued that AI and computer science education should begin early and be developmentally staged [4]. Together, these studies show that current AI literacy debates did not emerge abruptly with generative AI; rather, they build on a longer trajectory concerned with age-appropriate explanation, conceptual progression, and civic relevance.

For an interdisciplinary readership, several concepts also require clarification. Bloom's taxonomy refers to a hierarchy of learning processes that usually progresses from remembering and understanding toward applying, analyzing, evaluating, and creating. In AI literacy, the category of "recognizing AI" means being able to identify when an apparently ordinary digital service, such as a recommendation feed or voice assistant, is using AI techniques. Similarly, "hidden layers" are the intermediate computational layers in a neural network that transform inputs into increasingly abstract internal representations; they are important pedagogically because visualizing them helps learners see that AI outputs are produced through a layered process rather than through machine 'intuition.' A comparative overview of the major AI literacy frameworks discussed above is provided in **Table 1**.

Table 1. Comparison of Major AI Literacy Frameworks (2020–2024).

Framework	Components	Key Focus Areas	Target Audience
Long and Magerko (2020)	17 competencies across 5 themes	Technical understanding, critical evaluation, ethics	General public
Ng et al. (2021)	4 cognitive domains	Know, Use, Evaluate/Create, Ethics	K-12 students
UNESCO (2024)	15 competencies, 5 dimensions	Human-centered mindset, ethics, pedagogy	Teachers & Students
Chiu et al. (2024)	5 key components	Technology, impact, ethics, collaboration, self-reflection	K-12 education
Almatrafi et al. (2024)	6 core constructs	Recognize, Know, Apply, Evaluate, Create, Ethics	All levels

Note: Frameworks have progressively expanded from technical focus to include ethical, social, and affective dimensions.

2.2. Science Communication in the AI Era

Science communication research provides essential theoretical grounding for understanding how complex technical knowledge can be effectively translated for public audiences. The field has evolved from deficit models—assuming public ignorance requiring correction through information dumping—to dialogic models emphasizing two-way engagement, contextualization, and meaning-making [12]. These evolved approaches are particularly relevant for AI literacy, where public understanding involves not merely factual knowledge but also attitudes, values, and practical capabilities. The deficit model fails in the context of AI because knowing how a neural network works does not inherently resolve public anxiety about job displacement; dialogic models, conversely, invite the public to interrogate why the technology is being deployed and who benefits from it.

The science communication lens becomes more persuasive when placed in dialogue with broader scholarship on public engagement. Bucchi and Trench emphasize that science communication is not only the transfer of information but also the negotiation of meaning between institutions and publics [5]. Davies et al. show that narrative, identity, and emotion shape how people encounter scientific knowledge [6], while Nisbet and Scheufele argue that framing, media environments, and public values strongly influence uptake [7]. These insights matter for AI literacy because people do not meet AI as neutral content; they meet it through news, platforms, museums, classrooms, and everyday anxieties about work, bias, and autonomy.

Related work on informal science learning also matters here. Research on museums, public participation, and audience-centered communication suggests that literacy is often built through situated experiences rather than through one-way instruction alone. For this reason, the present paper argues that AI literacy should include not only classroom teaching but also exhibitions, public workshops, participatory design activities, and community discussion formats that allow people to question, interpret, and contest AI in relation to their own lives.

Generative AI has fundamentally disrupted science communication ecosystems [13]. AI systems now generate science content, personalize information delivery, and serve as intermediaries between scientific knowledge and public audiences. The dual nature of AI in science communication creates unique challenges: AI can enhance information dissemination through personalization—tailoring complex explanations to a user's reading level—but also undermine it through hallucinations and the generation of plausible but false information. Moreover, AI acts as a communicative agent, entering the social sphere as an entity that appears to speak, reason, and create. This necessitates science communication approaches that address both AI's technical functioning (the object) and its implications for information ecosystems (the agent), teaching the public to navigate a world where non-human actors are primary sources of information.

2.3. Public Understanding and Trust in AI

Research on public perceptions of AI reveals a complex landscape characterized by enthusiasm, apprehension, and an AI trust paradox, where individuals use AI tools despite lacking trust in their mechanisms or governance [14]. Users frequently rely on algorithmic recommendations for navigation, entertainment, and even romantic matching, while simultaneously expressing deep distrust in the abstract concept of artificial intelligence and the corporations that control it. This paradox underscores the importance of science communication strategies that address both cognitive understanding and affective dimensions of AI literacy. Trust is not merely a function of technical reliability; it is also a function of perceived intent and accountability.

This argument also clarifies why science communication is more than one lens among many. An education-only perspective can teach users how to operate AI tools, but a science communication perspective foregrounds public-facing issues that technical instruction often underemphasizes: how claims are framed, how trust is negotiated, how uncertainty is communicated, how publics participate in decisions, and how institutions earn legitimacy. In this sense, AI literacy becomes not only a matter of knowing and using AI, but also of interpreting the communicative environment in which AI is explained, marketed, normalized, and contested.

Concerns about AI-generated misinformation have become particularly salient, creating a crisis of "epistemic trust." If the public cannot distinguish between a human-written scientific paper and an AI hallucination, the authority of science itself is threatened. Effective science communication must therefore go beyond technical explanation to build "epistemic trust"—helping the public understand how AI comes to its conclusions, the reliability of its data sources, and the limits of its capabilities. This involves "opening the black box" not just mathematically, but sociologically—revealing the human labor, data curation decisions, and institutional values that shape algorithmic outputs. Without this deeper level of literacy, the public remains vulnerable to both "AI hype" (overestimating capabilities) and "AI doomerism" (succumbing to paralyzed fear), rather than engaging in informed, critical adoption.

2.4. Learning Theories for AI-Mediated Communication

Two additional theoretical perspectives strengthen the framework's educational grounding. Cognitive Load Theory is relevant because AI concepts are often abstract, probabilistic, and jargon-rich [15]. A communication strategy informed by Cognitive Load Theory would reduce unnecessary complexity, sequence concepts from simple to complex, use visuals to externalize hidden processes, and avoid overloading learners with technical detail before they have a functional mental model. This helps explain why multimodal explanation, worked examples, and staged scaffolding are central to AI literacy design rather than merely optional teaching enhancements.

Vygotsky's Sociocultural Theory is equally important because AI literacy develops through dialogue, mediation, and participation in social practices [16]. Learners make sense of AI not only through individual cognition but also through conversation with teachers, peers, families, and communities. From this perspective, AI literacy is a socially distributed accomplishment shaped by language, culture, and institutional context. This is especially important when addressing cross-cultural differences in AI acceptance, trust, and ethics, which means that effective communication cannot assume a universal audience with identical concerns. Taken together, these learning theories help illustrate the convergence of AI literacy and science communication through pedagogical innovation (see **Figure 1**).

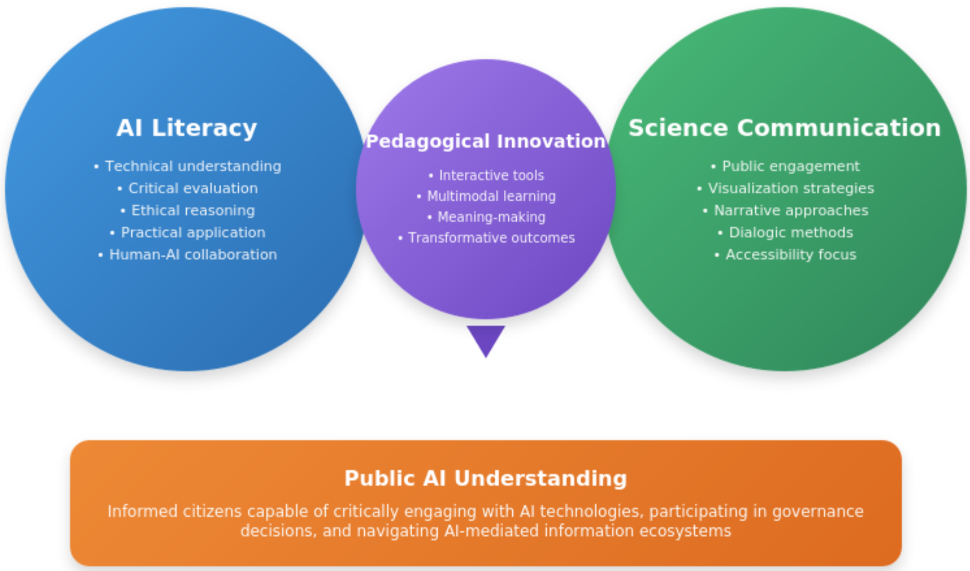

Figure 1. Integration Model: AI Literacy and Science Communication Convergence.

Note: The convergence zone represents pedagogical innovations as the mechanism linking AI literacy competencies with science communication strategies.

3. Literature Review: AI Literacy Education and Science Popularization

3.1. Current State of AI Literacy Education

Systematic reviews of AI literacy education reveal a landscape characterized by rapid but uneven growth. Casal-Otero et al. analyzed K-12 AI education implementations, finding a strong emphasis on fundamental concepts, machine learning logic, and practical applications [11]. However, this growth has been largely confined to formal education settings, creating a literacy silo where students inside specific curricula gain access to critical skills, while the broader public—including the working-age population and older adults—remains largely underserved. Most initiatives prioritize the how of AI over the why and what if, despite the latter being crucial for general citizenship. This disconnect creates a risk where the general public's understanding of AI is shaped more by sensationalist media narratives than by structured educational engagement.

Recent reviews also suggest that the field still privileges formal education over broader public communication. This is a significant limitation for a paper concerned with science communication, because public understanding is shaped not only in schools and universities but also through social media, cultural institutions, journalism, workplace training, and civic debate. Broadening the literature base, therefore, helps reposition AI literacy as a lifelong and public-facing process rather than as a curriculum issue only. This argument is reinforced by work on higher and adult education, as well as early childhood and community-facing AI education, which shows that developmental stage and learning environment substantially shape what counts as meaningful literacy [17,18].

Laupichler et al. conducted a comprehensive scoping review of AI literacy in higher and adult education, identifying a significant imbalance in assessment methodologies [17]. Their analysis revealed that while instruments for measuring technical knowledge are relatively robust, instruments measuring ethical reasoning, critical evaluation, and social impact awareness remain nascent and underdeveloped. This gap is problematic because AI literacy differs from traditional computer literacy; it requires subjective judgment about bias, fairness, and agency—competencies that are difficult to quantify with multiple-choice assessments. Consequently, current educational frameworks may be producing technically proficient users who lack the tools to critique the systems they are building or using.

3.2. Visualization and Interactive Tools for AI Understanding

Visualization represents a cornerstone of science communication strategy, particularly for fields dealing with high-dimensional, non-linear data like artificial intelligence. Because the mathematical operations inside a deep learning model are often unintuitive to the human mind, visualization acts as a critical translation layer. Yim and Su reviewed AI learning tools in K-12 contexts, identifying intelligent agents and glass-box interfaces as effective resources [19]. These tools allow users to open the black box of AI by visually manipulating training data and observing the immediate impact on model outputs. This experiential feedback loop is essential for demystifying abstract concepts like overfitting or bias, moving them from theoretical definitions to observable phenomena.

Interactive visualization tools enable learners to engage directly with AI concepts through hands-on experimentation, transforming passive consumers into active investigators. Williams et al. documented the effectiveness of integrated AI plus ethics curricula for middle school students, demonstrating meaningful learning gains in project-based settings [20]. By combining technical understanding with ethical reflection, students learned that ethics is not an external philosophical debate but an intrinsic property of the engineering process. From a multimedia learning perspective, these tools work best when visual, verbal, and interactive representations are deliberately coordinated rather than simply layered together.

In applied communication settings, such tools can also support what may be called digital nutrition labels: concise, audience-friendly disclosures that summarize what an AI system does, what data it relies on, what its likely limitations are, and where human oversight remains necessary. Like food labels, the purpose is not full technical disclosure for specialists, but interpretable guidance that supports everyday judgment. This is one concrete example of a pedagogical strategy that emerges from integrating AI literacy with science communication.

3.3. Pedagogical Approaches to AI Science Communication

Effective AI literacy education requires pedagogical approaches that balance technical accuracy with cognitive accessibility. Traditional computer science pedagogy often relies on bottom-up instruction, but AI literacy benefits from top-down, inquiry-based approaches. Analogies play a crucial role here; for example, comparing neural networks to biological brains provides a useful, albeit imperfect, scaffold for understanding connectionism. However, educators must carefully navigate these metaphors to avoid reinforcing anthropomorphic misconceptions. Embodied cognition—where learners physically act out algorithms, such as a group of students passing signals to simulate nodes in a network—can make abstract computational logic tangible and memorable.

The term constructionist approach here refers to learning by making: learners build or modify artifacts, reflect on the process, and thereby externalize abstract ideas in concrete form [21]. In AI literacy, this is useful not only because it deepens technical understanding, but also because it reveals sociotechnical assumptions embedded in datasets, interfaces, and evaluation metrics. The added value of a science communication perspective is that these design experiences are then interpreted in relation to audience, message, trust, and public consequence, rather than being treated solely as engineering exercises.

The "Students as AI Literate Designers" (SAILD) framework grounds AI literacy in design-based learning, enabling learners to develop understanding through the act of creation. In this model, students are not just analyzing AI; they are designing solutions to real-world problems, such as a chatbot to help school visitors or a vision system to sort recycling. This constructionist approach fosters a sense of agency and ownership. By encountering friction during the design process—such as a model failing to recognize an accent or an object—learners gain a nuanced appreciation for the fragility and limitations of AI systems. This "learning by debugging" cultivates a critical mindset that is essential for navigating an AI-saturated world.

3.4. Challenges in Current Approaches

Despite significant progress, the field faces systemic challenges that threaten to undermine the goal of universal AI literacy. First, the "digital divide" has evolved into a "computational divide." Access to high-quality AI literacy is unevenly distributed, not just due to a lack of hardware, but due to a lack of access to the high-performance computing resources and large datasets required to train modern models. This risks creating a two-tiered society where affluent learners understand and control AI, while marginalized communities are merely subject to its automated decisions.

Second, the pace of AI development creates a curriculum lag. Educational resources and textbook approval cycles operate on timelines of years, while the capabilities of generative AI evolve in weeks. This leads to the teaching of zombie concepts—methods or architectures that are technically interesting but practically obsolete in the face of rapid platform change. Educators struggle to maintain currency, often relying on outdated examples that fail to prepare students for the tools they will actually encounter.

A related omission in many current approaches is the lack of attention to everyday practice. For example, "AI hygiene" can be defined as the routine habits that reduce careless or harmful AI use: checking outputs against other sources, disclosing when AI has been used, protecting sensitive data, recognizing automation bias, and pausing before re-sharing synthetic content. Framed this way, AI literacy is not only a matter of mastering concepts but also of cultivating responsible communicative habits.

Third, there is a profound disconnect between the technical explanations provided by computer scientists and the social/ethical concerns prioritized by the public. Technical explanations often focus on optimization and accuracy, while public discourse centers on fairness, displacement, and trust. Bridging this gap requires a science communication perspective that prioritizes "sociotechnical relevance"—explaining not just how the algorithm minimizes error, but what that minimization means for human values. Current approaches often segregate these domains, treating ethics as a separate module rather than the context in which technical systems operate.

3.5. What a Science Communication Perspective Adds

The synthesis above suggests that AI literacy researchers miss at least three things when science communication theory is absent. First, they may overemphasize technical comprehension while underemphasizing framing, trust, participation, and audience interpretation. Second, they may treat communication as delivery rather than as dialogue, thereby overlooking how public concerns about power, employment, bias, surveillance, and authorship shape learning outcomes. Third, they may fail to connect formal instruction with informal settings such as museums, community forums, journalism, and online public discourse, where many people actually encounter AI for the first time.

Seen through this lens, concrete pedagogical strategies emerge that would be less visible in a purely technical framework: participatory explanation workshops, public-facing AI exhibits, comparative analyses of human- and AI-generated science messages, disclosure labels for AI-generated content, community dialogue formats, and reflective activities centered on trust, accountability, and interpretation. The COMMUNICATE framework is therefore intended to differentiate itself from existing models by linking AI literacy competencies to communicative settings, audience diversity, and public meaning-making.

4. The COMMUNICATE Framework

The eleven principles are not intended as an arbitrary acronym. They were derived by clustering recurring concerns in the reviewed literature: contextualization, dialogue, multimodal explanation, participatory meaning-making, accessibility, narrative, interactivity, critique, scaffolding, transformative application, and ethics. Their specific configuration reflects the paper's central claim that AI literacy should be designed not only for comprehension, but also for public interpretation and responsible participation. In that sense, COMMUNICATE differs from adjacent frameworks by explicitly integrating pedagogical design with science communication functions. As shown in **Table 2**, these eleven principles collectively define the structure and pedagogical intent of the COMMUNICATE framework.

Table 2. The COMMUNICATE Framework for AI Literacy as Science Communication.

Principle	Component	Description
C	Contextual Understanding	Situate AI concepts within learners' existing knowledge and experiences
O	Open Dialogue	Create spaces for questions, concerns, and diverse perspectives
M	Multimodal Representation	Employ visualizations, narratives, simulations, and hands-on experiences
M	Meaning-Making	Facilitate active sense-making connecting AI to personal relevance
U	Universal Accessibility	Ensure accessibility across demographics and educational backgrounds
N	Narrative Engagement	Leverage storytelling to engage attention and facilitate understanding
I	Interactive Exploration	Enable hands-on interaction with AI tools and concepts
C	Critical Evaluation	Develop capabilities to evaluate AI outputs and recognize limitations
A	Adaptive Scaffolding	Provide appropriate support structures for progressive understanding
T	Transformative Learning	Foster fundamental shifts in understanding and relating to AI
E	Ethical Reflection	Integrate ethical dimensions throughout AI understanding

Note: Each principle draws upon established science communication and AI literacy scholarship while addressing specific challenges of public-facing AI education.

Building upon the theoretical foundations and empirical evidence reviewed above, we propose the COMMUNICATE framework for AI literacy as science communication. This framework integrates principles from AI literacy research, science communication studies, and educational technology.

4.1. Contextual Understanding (C)

AI literacy must be firmly situated within learners' lived experiences to be effective. Abstract definitions of algorithms often alienate non-technical audiences; therefore, education should begin by reverse-engineering the AI tools learners already encounter in their daily lives. By deconstructing familiar interfaces—such as social media feeds, movie recommendation engines (e.g., Netflix), and voice assistants (e.g., Siri, Alexa), and navigation apps—educators can demonstrate that AI is not a distant, futuristic concept but an invisible infrastructure already shaping human behavior. This approach of "contextual anchoring" helps counter the "magic" narrative often associated with AI, grounding the technology in tangible, relatable applications before introducing complex underlying mechanics.

4.2. Open Dialogue (O)

Effective science communication requires a fundamental shift from the "deficit model" of one-way transmission to a "dialogic model" of engagement. This involves creating safe, inclusive forums—both physical (e.g., science cafés, town halls) and digital—where the public can freely express anxieties regarding job displacement, surveillance, and loss of human agency. Acknowledging and addressing these affective dimensions is a prerequisite for cognitive learning; dismissing public fears as "irrational" often deepens resistance to scientific information. True open dialogue views the learner not as an empty vessel to be filled, but as a participant with valid concerns that can shape the learning trajectory, allowing for the co-creation of knowledge that is socially robust.

4.3. Multimodal Representation (M)

Complex AI concepts are often abstract and mathematical, necessitating the use of multiple representational formats to reduce cognitive load and enhance comprehension. Research in cognitive science, particularly dual coding theory, demonstrates that combining text, audio, and visuals significantly improves retention. AI literacy initiatives should employ interactive visualizations to illustrate algorithmic processes—for instance, visualizing the "landscape of loss" in gradient descent as a hiker finding the lowest point in a valley, or showing how a Convolutional Neural Network (CNN) progressively identifies edges, textures, and shapes. Beyond the visual, sonification (representing data as sound) and physical metaphors can further bridge the gap between abstract code and human understanding.

4.4. Meaning-Making (M)

True literacy transcends rote memorization; it is constructed through active meaning-making where learners connect technical concepts to personal values and societal implications. This dimension emphasizes "sociotechnical literacy"—understanding AI not just as code, but as a system involving people, data, and institutions. For instance, understanding the technical definition of "bias in training data" becomes profoundly meaningful when connected to real-world examples of algorithmic discrimination in hiring, lending, or healthcare. Facilitating this meaning-making process transforms AI from a dry technical subject into a relevant social issue, fostering a deeper, more enduring engagement with the material.

4.5. Universal Accessibility (U)

AI literacy initiatives must be universally accessible, transcending barriers of demographics, language, and physical ability. This requires a commitment to Universal Design for Learning principles, ensuring that educational materials are available in diverse formats and languages while avoiding unnecessary jargon that acts as a gatekeeper [22]. Furthermore, addressing the digital divide is paramount; unplugged AI education—using paper, cards, or physical games to teach algorithmic logic—ensures that learners in low-resource environments or without reliable internet access are not excluded. Cultural relevance is also critical; examples and case studies should resonate with diverse global communities, moving beyond Western-centric narratives to include local applications and perspectives.

4.6. Narrative Engagement (N)

Storytelling is a potent cognitive tool for organizing information and fostering engagement in science communication. Narratives can effectively illustrate the potential futures of AI, helping the public visualize abstract risks and benefits in concrete terms. While science fiction has traditionally shaped public perception, educators can leverage "design fiction" and "speculative design" to create grounded, provocative scenarios—such as a fictional future news report or a user manual for a non-existent AI product—to spark debate. Moving beyond the binary tropes of "utopian salvation" or "existential termination" allows for more nuanced storytelling that explores the complex, messy reality of human-AI coexistence.

4.7. Interactive Exploration (I)

Hands-on interaction transforms learners from passive recipients of information into active investigators and "algorithmic auditors." The use of "sandbox" environments—where users can experiment with AI models without consequence—is essential. Tools that allow users to intentionally "break" an AI model, such as feeding it adversarial examples (images with slight noise that confuse the system) or testing the limits of a chatbot, are particularly effective. This "learning by breaking" approach reveals the fragility and limitations of AI systems, countering the myth of infallibility and teaching the concept of robustness through direct, visceral experience.

4.8. Critical Evaluation (C)

Critical evaluation acts as the "immune system" of the information age, protecting individuals from manipulation and misinformation. In the context of AI, this goes beyond standard media literacy to include "AI hygiene"—understanding the probabilistic nature of generative models (i.e., they are pattern completers, not truth-tellers). Competencies include "lateral reading" (verifying claims across multiple sources), recognizing the "hallucination" phenomenon as a feature rather than a bug of current architectures, and "prompt auditing"—assessing how the framing of a question influences the AI's output. Developing these critical faculties empowers users to navigate the AI landscape with skepticism and discernment.

4.9. Adaptive Scaffolding (A)

Education should meet learners where they are, employing adaptive scaffolding to build competence incrementally. Following Bruner's spiral curriculum, concepts can be revisited at increasing levels of complexity. The progression might start with a "black box" approach (observing inputs and outputs to understand capability), move to a "glass box" visualization (seeing the internal weights and activations to understand mechanism), and finally to a "white box" level (modifying the code itself). UNESCO's progression from "Acquire" to "Deepen" to "Create" exemplifies this structured approach, ensuring that learners are not overwhelmed by technical complexity before grasping fundamental principles.

4.10. Transformative Learning (T)

The ultimate goal of AI literacy is transformative learning—a fundamental shift in perspective that alters how individuals view their relationship with technology. This involves moving from a "passive consumer" mindset, where

AI is viewed as magic or an inevitable force, to an "active citizen" mindset, where AI is understood as a human-designed tool with specific affordances and constraints. This transformation empowers individuals to reclaim agency, understanding that they have the right to question, refuse, or demand accountability from AI systems. It cultivates the confidence to participate meaningfully in democratic decisions regarding AI governance and regulation.

4.11. Ethical Reflection (E)

Ethical reflection should not be treated as a separate module or an afterthought but must be woven throughout the entire educational fabric. When learning about datasets, learners should be prompted to ask: "Who collected this data? Who is represented, and who is erased?" When exploring optimization algorithms, the inquiry should be: "Optimization for whom? At what environmental or social cost?" This integration of "ethics by design" into literacy education helps learners identify the "hidden curriculum" of values embedded in technical systems, fostering a generation of users and creators who prioritize human rights and social justice in the algorithmic age. Taken together, these eleven dimensions form the integrated COMMUNICATE framework shown in **Figure 2**.

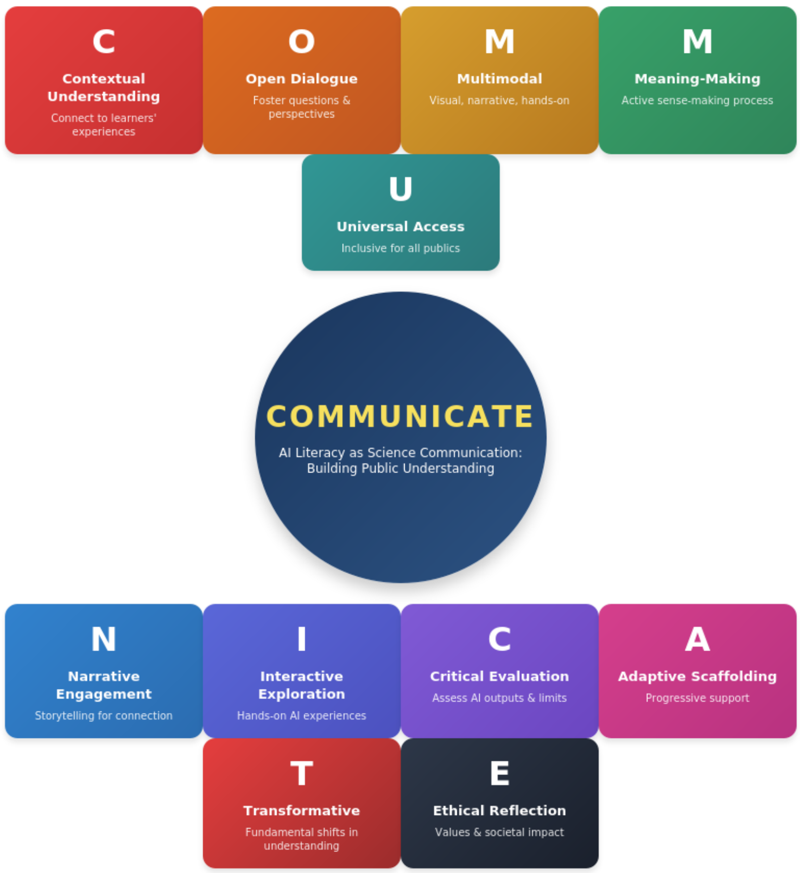

Figure 2. The COMMUNICATE Framework for AI Literacy as Science Communication.

4.12. Operationalizing the Framework

To quantify the impact of the COMMUNICATE framework, future research must move beyond simple knowledge-retention quizzes. One possible direction is the development of a multidimensional AI Literacy Index that captures not just technical recall but the ability to apply concepts in novel, real-world scenarios. Assessment strategies should therefore include scenario-based evaluation, reflective explanation, and performance tasks that test whether learners can audit a system for bias, interpret uncertainty, or navigate a deepfake encounter. This multi-dimensional operationalization would better match the framework's public-communication goals.

At the same time, this proposal should be interpreted cautiously. The framework has not yet been validated through large-scale intervention studies, and alternative configurations may also prove useful. "Ethics by design" is therefore treated here as a guiding principle for implementation and evaluation, not as evidence that the framework has already solved the ethical and pedagogical challenges surrounding AI communication.

5. Implementation Strategies for AI Literacy as Science Communication

5.1. Visualization Strategies for Public AI Understanding

Effective visualization is essential for bridging the gap between mathematical abstraction and public understanding, but it requires a careful balance of simplifying without distorting. For machine learning, metaphors must be chosen to illuminate rather than obscure; for instance, visualizing the "training" process as a landscape where the model acts as a hiker seeking the lowest point of error (gradient descent) uses intuitive 3D terrain concepts to explain complex optimization. However, educators must caution against anthropomorphic visualizations that ascribe human intent to statistical processes.

Platforms like the TensorFlow Playground demonstrate the power of interactive visualization, allowing users to tweak parameters and watch the decision boundary shift in real time. This provides immediate, visual feedback on cause-and-effect relationships within a neural network. In museums and public engagement settings, similar strategies can be linked to the experiential learning logic described by Falk and Dierking, who emphasize the importance of context, prior knowledge, and personal meaning in informal learning environments [23].

Accordingly, one implementation pathway is to pair explanatory visualizations with short interpretive prompts or digital nutrition labels that tell audiences what is being simplified, what data are omitted, and what forms of uncertainty remain. This aligns visualization with science communication's emphasis on transparency and audience interpretation rather than mere display.

AI literacy must extend beyond the formal classroom to reach the general public where they gather. Science museums and science centers are especially promising venues for this work, and professional guidance from the Association of Science and Technology Centers reinforces the importance of audience-centered, activity-based AI learning in such environments [24]. Interactive exhibits can allow visitors to see what a computer vision system detects, where it fails, and how training data shape those outcomes.

AI literacy must extend beyond the formal classroom to reach the general public where they gather. Science museums and science centers are ideal venues for this, offering "explainable AI" exhibits where visitors can physically interact with computer vision systems to see what the machine "sees"—and crucially, where it fails. For example, an interactive exhibit might allow visitors to train a simple pose-estimation model, intentionally introducing biased data (e.g., only training on adults) to observe how the model subsequently fails to recognize children. This experiential learning cements the concept of "data bias" far more effectively than a lecture.

Libraries, too, are evolving into critical hubs for digital citizenship. Beyond books, they can serve as community laboratories for "algorithmic auditing" workshops, where citizens collectively test local government or commercial algorithms for fairness. Collaborative learning environments in makerspaces can empower users to build simple, transparent AI models using low-code tools, fostering a sense of ownership. By embedding AI literacy into existing community infrastructures—including senior centers and youth clubs—we normalize the technology and provide a safe, supported environment for exploration away from the pressure of academic assessment.

This is also where the science communication angle most clearly changes practice. In informal settings, the goal is not simply to transfer curriculum content but to facilitate curiosity, conversation, and situated reflection among heterogeneous publics. Audience-centered approaches from museum and public engagement research can therefore help tailor AI literacy activities to families, adult learners, community organizations, and visitors with very different prior knowledge and cultural expectations.

In practical terms, this section can be understood as the cultivation of AI hygiene. Learners should be taught to verify sources, compare outputs across systems, disclose AI assistance when appropriate, avoid uploading sensitive material without reflection, and recognize when fluency or confidence in AI-generated language is masking weak evidential support.

In an era of deepfakes and hallucinating language models, addressing misinformation requires proactive strategies. "Prebunking" or inoculation theory suggests that exposing people to weakened, transparent examples of AI manipulation helps them build resistance to actual malicious content. AI literacy campaigns should include "redteaming" exercises where participants actively try to generate fake news or realistic-looking images using AI tools. By understanding the mechanism of creation—how easy it is to manipulate voice, tone, and imagery—participants become more skeptical consumers.

However, relying solely on visual "tells" (like extra fingers in AI images) is a diminishing strategy as technology improves. Therefore, literacy must shift focus toward "contextual verification" and provenance. Science communicators should educate the public on emerging standards like C2PA (content credentials) and digital watermarking, explaining them as "digital nutrition labels" for information. The goal is to cultivate a habit of "provenance checking"—asking where a piece of content came from and how it was processed—rather than just trusting one's eyes. This shift from sensory verification to systemic verification is crucial for long-term epistemic trust.

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5.2. Addressing the Digital Divide

A critical implementation challenge is the digital divide, which threatens to create a two-tiered society of AI "haves" and "have-nots." High-end AI tools often require expensive hardware, high-speed internet, or paid subscriptions, excluding vast segments of the global population. Implementation strategies must therefore be radically inclusive. This involves low-resource optimization, prioritizing the development of "TinyML" educational tools that can run on basic smartphones or even microcontrollers without a constant internet connection, ensuring that learners in the Global South or rural areas are not left behind.

Furthermore, unplugged activities—teaching computational concepts without computers—are vital. Games that simulate neural networks using decks of cards, or group activities where participants physically act out the role of "nodes" passing information, can teach the logic of algorithms and weights without requiring a single screen. Finally, we must invest in community-based intermediaries. By training librarians, community leaders, and local teachers as "AI literacy ambassadors," we create trusted human bridges who can translate complex concepts into local languages and cultural contexts, ensuring that AI literacy is not just a privilege for the tech-savvy elite but a fundamental right for all.

The distinctive contribution of the present paper is therefore not simply to restate that AI should be taught responsibly, but to argue that public understanding, trust, and participation should be treated as design criteria for AI literacy efforts. This reorients communication from explanation alone toward explanation-plus-engagement. Recent work on generative AI, learning analytics, and pedagogy further underscores the need for transparent, critically reflective, and evidence-sensitive integration strategies in educational settings [25–27].

6. Discussion and Implications

6.1. Implications for Science Communicators

Reconceptualizing AI literacy as a branch of science communication fundamentally alters the professional mandate of the field. Science communicators must evolve beyond their traditional role as explainers of established facts to become "technological bilinguals," fluent in both the computational logic of machine learning and the social values of their diverse audiences. This "bilingualism" requires the ability to translate technical concepts like "loss functions" or "gradient descent" into meaningful social narratives without losing accuracy. For instance, explaining algorithmic bias not merely as a statistical error but as a reflection of historical societal inequities embedded in training data.

The distinctive contribution of the present paper is therefore not simply to restate that AI should be taught responsibly, but to argue that public understanding, trust, and participation should be treated as design criteria for AI literacy efforts. This reorients communication from explanation alone toward explanation-plus-engagement.

Furthermore, science communicators face a unique "dual burden": they must explain AI while increasingly using AI tools to create content. This necessitates a new ethical standard of practice—a "meta-transparency" where the use of AI in the communication process itself is disclosed. If a summary is generated by a large language model (LLM), the communicator must verify its accuracy and disclose its provenance, modeling the very transparency they advocate for. The danger of "AI hype" versus "AI doomerism" also positions the science communicator as a crucial stabilizer;

they must resist the media pressure to anthropomorphize AI as "thinking" entities, instead consistently framing them as sophisticated probability engines. This requires close, ongoing collaboration with computer scientists to ensure that metaphors (like "neural networks") do not mislead the public into believing these systems possess biological sentience.

6.2. Implications for Educators

For educators, the shift to AI literacy requires a pedagogical transformation from "coding-centric" to "comprehension-centric" models. While learning to code remains valuable, the priority for general citizenship is "systemic thinking"—understanding how AI systems interact with, influence, and sometimes disrupt social systems. Meaning-making must take precedence over the rote memorization of technical syntax. In the classroom, this means replacing abstract programming exercises with "algorithmic case studies." For example, rather than just building a classifier, students might analyze a real-world dataset of loan applicants to identify why a model might systematically deny loans to specific demographic groups, thereby learning about feature weighting and proxy variables in a socially relevant context.

Assessment strategies must also undergo a radical redesign. Traditional multiple-choice tests are ill-suited for measuring the fluid, critical skills required for AI literacy. Educators should pivot toward performance-based assessments and portfolios. A student might be tasked with "auditing" a new AI tool, documenting its limitations, potential biases, and data sources, or redesigning a user interface to make an algorithm's decision-making more transparent. Furthermore, the rapid pace of AI evolution creates a professional development crisis; teacher training cannot be a one-time certification but must be an agile, ongoing process. Curriculum resources need to be dynamic—updated monthly rather than yearly—to remain relevant, requiring a shift in how educational materials are produced and distributed.

6.3. Policy Implications

To further validate and refine the COMMUNICATE framework, future research must expand in scope and methodology. More specifically, future work could test whether dialogic activities improve trust calibration, whether disclosure labels improve critical evaluation, whether multimodal visualizations reduce cognitive overload, and whether public-participation formats increase long-term retention and civic efficacy. These are empirical questions that can be studied through interventions, design experiments, surveys, and mixed-method evaluations.

Moreover, policy must support literacy through regulation that enforces transparency. A "right to understand" should be codified, mandating that AI deployments in public sectors (like justice or welfare) be explainable to those affected. Policymakers should push for "nutritional labels" on AI models—standardized disclosures of training data sources, model architecture, and known limitations. Such regulation aids literacy by providing the public with consistent, reliable information to evaluate the tools they encounter. Finally, workforce development policies must recognize that an AI-literate workforce is a macroeconomic imperative; the ability to collaborate effectively with AI systems will soon be a baseline requirement for economic participation across all sectors.

6.4. Future Research Directions

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More specifically, future work could test whether dialogic activities improve trust calibration, whether disclosure labels improve critical evaluation, whether multimodal visualizations reduce cognitive overload, and whether public-participation formats increase long-term retention and civic efficacy. These are empirical questions that can be studied through interventions, design experiments, surveys, and mixed-method evaluations.

Longitudinal Studies: We need robust longitudinal research to measure the retention and decay of AI literacy competencies over time. As "generative AI" evolves into "agentic AI," do the foundational skills taught today remain relevant? Tracking cohorts over years will reveal whether current pedagogical interventions produce durable critical thinking skills or merely transient technical familiarity.

Cross-Cultural Comparisons: Research must investigate how cultural values influence the reception of AI metaphors and the definition of "trust." For example, do collectivist cultures, which may prioritize social harmony, perceive "AI alignment" and surveillance differently than individualist cultures that prioritize privacy? Understanding these nuances is critical for developing global AI literacy standards that respect local values rather than imposing a Western-centric worldview.

Impact on Behavior: Moving beyond self-reported confidence, researchers must measure actual behavioral changes. Does increased AI literacy lead to safer online behaviors, such as better password hygiene or reduced sharing of misinformation? Does it lead to more active civic participation, such as submitting comments on AI regulations? We need experimental designs that test whether literate citizens actually resist manipulation when confronted with sophisticated deepfakes in the wild.

Pedagogical Efficacy: Finally, rigorous randomized control trials (RCTs) are needed to compare the efficacy of different instructional approaches. For instance, do "unplugged" (paper-based) activities effectively teach neural network logic to non-technical audiences, or are high-tech simulations necessary? Establishing an evidence base for how to teach AI literacy is just as important as defining what to teach.

6.5. Limitations

Several limitations should be acknowledged explicitly. First, the COMMUNICATE model is a conceptual framework derived from literature synthesis rather than from primary empirical testing, so its practical effectiveness remains to be demonstrated. Second, although this revision broadens the review base, the synthesis is still selective and interpretive rather than exhaustive in the strict systematic-review sense. Third, some assumptions about trust, accessibility, and participation may vary across cultural and institutional settings, meaning that the framework should be adapted rather than transplanted wholesale. Finally, implementation feasibility is uneven: schools, museums, and community organizations differ substantially in resources, policy support, staff preparation, and technical infrastructure.

7. Conclusions

As artificial intelligence technologies transition from novel curiosities to pervasive infrastructure—underpinning everything from healthcare diagnostics to creative expression—developing robust public AI literacy has escalated from an educational goal to a critical societal imperative. This paper has advanced the central argument that AI literacy must be reconceptualized not merely as a skill acquisition task for computer science, but as a fundamental domain of science communication. By reframing the challenge through this lens, we move beyond the limited goal of training 'users' to the broader democratic objective of cultivating informed 'citizens' capable of navigating an algorithmic society.

The proposed COMMUNICATE framework offers a comprehensive roadmap for this pedagogical transformation, guiding educators and communicators to move beyond dry technical instruction toward holistic, socially situated understanding. By rigorously integrating contextual anchoring, dialogic engagement, and deep ethical reflection, and by leveraging the power of innovative visualization and narrative strategies, we can demystify the 'black box' of AI. This approach ensures that literacy initiatives do not simply teach how to operate tools, but illuminate the underlying logic, limitations, and values embedded within them.

For that reason, the value of COMMUNICATE lies less in claiming finality than in offering a traceable, theory-informed agenda for designing, comparing, and empirically testing AI literacy interventions across classrooms and public settings. The framework should be understood as a structured starting point for interdisciplinary collaboration among educators, science communicators, designers, and policymakers.

Ultimately, the success of this endeavor will be measured by our ability to empower the public with true agency. A scientifically literate populace does not merely accept AI as an inevitable force of nature; rather, they possess the critical faculties to question its outputs, challenge its biases, and demand accountability from its creators. By fostering this depth of understanding, we ensure that the future of human-AI interaction is not dictated solely by technological capability, but is shaped by informed public discourse and human-centered values. The time to build this foundation is now, as the decisions we make today about public understanding will define the trajectory of our shared digital future.

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Conflicts of Interest

The author declares no conflict of interest.

AI Use Statement

During the preparation and revision of this manuscript, generative AI tools were used solely for language refinement and editorial assistance. No AI tools were used for data analysis, interpretation, or generation of scientific claims. All content was critically reviewed and edited by the author, who takes full responsibility for the integrity and accuracy of the work.

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