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A Community-Based STEM Model for Algorithmic Literacy: The Educational Role of Public Libraries in AI Learning

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Abstract

Artificial intelligence systems increasingly shape scientific knowledge production, information access, and civic participation. Traditional digital literacy frameworks are insufficient for understanding algorithmically mediated environments, which requires a STEM-oriented approach to algorithmic literacy. This study proposes and designs a community-based STEM education model implemented within public library settings. The model integrates elements of inquiry-based learning, critical data analysis, and applied AI literacy activities aimed at developing conceptual understanding of algorithms, data bias, and automated decision-making systems. The instructional framework combines non-formal STEM education, problem-based learning scenarios, and facilitator-guided exploration of AI tools. A pilot implementation design is presented, including learning objectives, competency mapping, and evaluation indicators for measuring gains in algorithmic literacy. The findings suggest that libraries can function as decentralized STEM learning hubs, extending science education beyond formal school environments and contributing to more equitable access to AI-related knowledge.

Keywords: *Algorithmic Literacy; STEM Education; Artificial Intelligence; Science Teaching Models; Public Libraries*

1. Introduction

Artificial intelligence (AI) systems have become deeply embedded in contemporary scientific practice, information ecosystems, and everyday civic life. Recommendation algorithms determine which news citizens encounter; automated decision-making systems allocate social services and credit; large language models co-author scientific papers and educational content. Yet the majority of citizens lack the conceptual tools to understand, critique, or meaningfully engage with these systems. A 2021 study found that fewer than 4% of surveyed individuals could confidently explain how AI works [12], a figure that underscores a growing epistemic divide between those who design algorithmic systems and those who are subject to them.

Traditional digital literacy frameworks, while valuable, are insufficient to address this challenge. Understanding algorithmically mediated environments requires a fundamentally different cognitive toolkit – one grounded in STEM reasoning, data interpretation, statistical thinking, and scientific inquiry. Algorithmic literacy, understood as the capacity to understand, evaluate, and critically engage with algorithmic systems, is increasingly recognized as a foundational competence of the 21st century [12, 8]. The European DigComp 3.0 framework has already incorporated competencies related to AI and data, acknowledging that working with algorithmic systems is now a core dimension of digital participation [13].

Public libraries occupy a distinctive and underutilized position in this landscape. As trusted civic institutions with a mandate to provide equitable access to knowledge, libraries have historically served as sites of informal and non-formal learning for populations excluded from formal educational pathways. Their infrastructure, community relationships, and professional ethos make them natural candidates for becoming decentralized STEM learning hubs – spaces where algorithmic literacy can be developed by a broad and diverse public.

This article proposes a community-based STEM education model for algorithmic literacy, designed specifically for implementation within public library settings. The model integrates inquiry-based learning, critical data analysis, problem-based scenarios, and hands-on AI tool exploration. It presents a pilot implementation design including learning objectives, competency mapping aligned with established frameworks, and evaluation indicators. The study addresses three research questions:

- Can targeted STEM-based AI literacy programs in public libraries significantly improve participants' conceptual understanding of algorithms, data bias, and automated decision-making?

- Does library-based AI education foster more informed, critical, and agency-oriented attitudes toward AI systems?
- Can library professionals, with appropriate facilitation training, effectively deliver STEM-oriented AI literacy programming to community members?

2. Theoretical Framework

2.1 Algorithmic Literacy as a STEM Competence

Algorithmic literacy has emerged as a distinct construct in the broader landscape of digital and AI literacy research. While digital literacy typically encompasses skills for using digital tools, and media literacy focuses on critical consumption of media content, algorithmic literacy addresses the specific capacities required to understand and critique automated systems that make consequential decisions about information access, resource allocation, and social participation [9].

The STEM framing of algorithmic literacy is significant. At its core, engaging with algorithms requires scientific thinking: forming hypotheses about how systems behave, testing them against evidence, interpreting data, and reasoning about causality and correlation. Understanding data bias – one of the central concerns of AI literacy – requires statistical literacy and the ability to reason about sample representativeness, measurement validity, and distributional fairness.

Long and Magerko (2020) [8], in their influential framework for AI literacy, identify seventeen competencies organized around what AI can and cannot do, how it works, and how citizens can critically evaluate and interact with AI systems. Their framework explicitly incorporates STEM concepts including data collection and classification, learning from data, statistical generalization, and the evaluation of model performance. Similarly, the UNESCO Competency Framework for AI in Education (2022) [14] emphasizes computational thinking, data literacy, and problem-solving as prerequisites for meaningful AI engagement.

The European DigComp 3.0 framework, updated in 2022 [2], integrates AI-related competencies into its broader digital competence model, including the ability to critically evaluate AI-generated content, understand how personal data is used by algorithmic systems, and participate in democratic debates about AI governance [13]. These frameworks collectively suggest that algorithmic literacy is not merely a technical skill set but a STEM-inflected civic competence essential for full participation in contemporary knowledge societies.

2.2 Non-Formal STEM Education And Inquiry-Based Learning

Non-formal STEM education – learning that occurs outside formal school curricula but within structured program environments – has been extensively studied as a mechanism for extending science education to underserved populations. Research consistently demonstrates that informal and non-formal science learning environments, including libraries, museums, science centers, and community organizations, can produce significant gains in scientific understanding, science identity, and motivation for further learning [10].

Inquiry-based learning (IBL), a pedagogical approach in which learners are guided to construct knowledge through investigation, experimentation, and reflection, is particularly well-suited to algorithmic literacy education. Rather than transmitting declarative knowledge about how algorithms work, IBL invites participants to pose questions, explore AI tools, interpret outputs, and form evidence-based conclusions. This approach cultivates both conceptual understanding and epistemic agency – the capacity to evaluate knowledge claims independently.

Problem-based learning (PBL), a related approach in which learners engage with authentic, complex problems that require integration of multiple knowledge domains, is similarly appropriate for AI literacy contexts. Real-world scenarios involving algorithmic decision-making – such as bias in hiring algorithms, filter bubbles in social media, or errors in automated medical diagnosis – provide motivating and contextually rich entry points for learning. PBL has been shown to enhance transfer of learning, critical thinking, and collaborative problem-solving skills [5].

Public libraries have a long tradition of implementing non-formal learning programs. From children’s reading programs to digital literacy workshops for adults, libraries have demonstrated capacity to design and deliver structured learning experiences for diverse populations. The integration of STEM-oriented AI literacy into this existing tradition represents a natural extension rather than a departure from the library’s educational mission.

2.3 Libraries as Decentralized STEM Learning Hubs

The concept of libraries as STEM learning hubs has gained increasing traction in library science and science education research. The International Federation of Library Associations and Institutions (IFLA) has explicitly positioned libraries as critical infrastructure for AI literacy, noting that their unique combination of public trust, physical accessibility, and non-commercial orientation makes them ideal venues for community AI education [6].
Libraries possess several structural advantages for STEM-oriented algorithmic literacy programming. They are geographically distributed, with branches often located in communities with limited access to formal educational institutions. They serve populations across the full age spectrum, enabling intergenerational learning. They operate without admissions barriers, tuition fees, or credential requirements. And they employ information professionals with expertise in knowledge organization, source evaluation, and instructional facilitation – competencies that transfer naturally to algorithmic literacy education.
Empirical evidence supports the efficacy of library-based STEM programming. Studies of library makerspaces, coding clubs, and science activity programs demonstrate that library-based interventions can improve STEM knowledge, increase science self-efficacy, and reduce STEM identity gaps among underrepresented populations [1]. These findings provide a basis for cautious optimism about the potential of library-based algorithmic literacy programs, while acknowledging that AI literacy presents distinctive challenges that warrant purpose-specific instructional design.

3. Model Design: A Community-Based STEM Framework for Algorithmic Literacy

3.1 Design Principles

The proposed model is grounded in six design principles derived from the theoretical framework and from analysis of existing library-based AI literacy initiatives:

- **STEM integration:** activities are explicitly framed within scientific inquiry, data reasoning, and computational thinking rather than purely technical skills training;
- **Inquiry-first pedagogy:** each module begins with a question or problem, not an explanation; learners are invited to investigate before being offered conceptual frameworks;
- **Critical perspective:** the model foregrounds issues of bias, fairness, transparency, and power as central content areas;
- **Accessibility and differentiation:** materials are designed for participants without technical backgrounds, with optional extension activities for more advanced learners;
- **Facilitator empowerment:** library professionals are positioned as learning facilitators, not subject-matter experts, reducing barriers to program adoption;
- **Community relevance:** case studies and scenarios are drawn from locally relevant contexts, including Bulgarian and European examples of algorithmic decision-making.

3.2 Competency Framework Alignment

The model is aligned with three established competency frameworks: the Long and Magerko (2020) AI Literacy Framework [8], the UNESCO AI Competency Framework for Students (2022) [14], and DigComp 3.0 (European Commission 2022) [2]. Table 1 presents the competency mapping across the five program modules.

Module	Long & Magerko (2020) Competencies	UNESCO AI Framework (2022)	DigComp 3.0 Area
1. What is an Algorithm?	Understanding AI; Representation; General vs. Narrow AI	Conceptual understanding of AI; Computational thinking foundations	2.2 Evaluating digital content; 5.1 Solving technical problems
2. Data and Bias	Data literacy; Critically evaluating AI outputs; Identifying bias	Data and privacy; Bias and fairness in AI systems	1.3 Engaging with digital content; 4.2 Protecting personal data
3. Hands-On AI Exploration	Using and interacting with AI; Understanding limitations	AI application literacy; Evaluating AI tool outputs	2.2 Evaluating content; 5.3 Creatively using digital technologies

4. Ethics & Accountability	AI ethics; Accountability; Societal impact of AI	Ethics of AI; Rights and regulation in AI environments	2.4 Protecting health and well-being; 2.6 AI and society awareness
5. Citizen Agency	Collaborating with AI; Civic participation in AI governance	AI governance; Lifelong AI learning skills	2.5 Protecting the environment; 4.3 Protecting health and rights

Table 1. Competency Mapping: Program Modules and Framework Alignment

3.3 Program Structure and Learning Objectives

The program consists of five modules, each designed for a three-hour session delivered weekly over five weeks, for a total of fifteen instructional hours. Sessions are designed for groups of 15–20 participants and can be delivered in a library reading room or computer lab equipped with projector and internet access.

Module 1: What is an Algorithm? Foundations of Computational Thinking

Learning objectives: Participants will be able to (1) define an algorithm and provide everyday examples; (2) explain the basic concept of machine learning; (3) distinguish between deterministic and probabilistic algorithmic systems.

Inquiry prompt: "How does Netflix know what you want to watch?"

Activities include a card-sorting exercise in which participants sequence instructions to complete a familiar task (a recipe, a route), followed by facilitator-guided exploration of a simple decision tree built from participant-provided examples. The session concludes with a structured discussion of what makes algorithmic decisions different from human decisions.

Module 2: Data and Its Discontents – Bias, Representation, and Missing Voices

Learning objectives: Participants will be able to (1) explain what training data is and how it shapes algorithmic outputs; (2) identify at least two mechanisms through which bias enters algorithmic systems; (3) critically evaluate claims about algorithmic objectivity.

Inquiry prompt: "If a computer learned only from old books, what would it think about women in science?"

This module situates data bias within social and historical contexts. Activities include analysis of real-world cases of documented algorithmic bias (e.g., COMPAS recidivism algorithm, gender bias in image search results) using primary sources. Participants conduct a structured data audit of a publicly available dataset, identifying missing categories and potential sources of misrepresentation. This module explicitly addresses statistical literacy components of algorithmic understanding, including concepts of representativeness, measurement error, and distributional fairness.

Module 3: How AI Tools Work in Practice – Hands-On Exploration

Learning objectives: Participants will be able to (1) use at least two AI tools (e.g., text generation, image recognition) and describe their observed behavior; (2) formulate and test hypotheses about AI tool outputs; (3) identify limitations and failure modes in AI-generated content.

Inquiry prompt: "Can you fool the machine? What does that tell us about how it works?"

Using freely available AI tools – including large language model interfaces, image classifiers, and translation systems – participants conduct structured experiments designed to probe system behavior. Working in pairs, they formulate predictions about how the system will respond to specific inputs, test those predictions, and document results. The "Human or Machine?" activity, in which participants evaluate whether text or image samples were produced by a human or an AI, provides an engaging entry into issues of AI output quality and detectability. The IBL structure of this module – predict, test, observe, explain – mirrors the scientific method and makes explicit the STEM framing of the inquiry.

Module 4: Automated Decisions and Their Consequences – Ethics and Accountability

Learning objectives: Participants will be able to (1) describe at least three domains in which automated decision-making affects citizens' lives; (2) articulate the concepts of transparency, explainability, and accountability in AI systems; (3) identify relevant European and Bulgarian regulatory frameworks (e.g., EU AI Act, GDPR).

Inquiry prompt: "If an algorithm denied your loan application, would you have the right to know why?"

This module engages participants with the governance dimensions of AI, grounding abstract ethical principles in concrete scenarios. Case studies include automated social benefit allocation, content moderation decisions, and algorithmic profiling in insurance. Participants engage in a structured deliberation exercise, taking assigned positions in a simulated public hearing about the deployment of an automated hiring system. The EU AI Act (2024) [3], which categorizes AI applications by risk level and mandates transparency requirements for high-risk systems, provides a current and locally relevant policy framework for discussion.

Module 5: Citizens in the Algorithmic Age – Agency, Advocacy, and Lifelong Learning

Learning objectives: Participants will be able to (1) identify practical strategies for protecting privacy and exercising rights in algorithmic environments; (2) articulate how citizens can participate in democratic debates about AI governance; (3) identify resources for continued learning about AI.

Inquiry prompt: "What can one person do about algorithms they disagree with?"

The final module moves from analysis to agency. Participants learn practical privacy hygiene strategies, explore options for algorithmic opt-out and data access requests under GDPR, and discuss models of collective action around AI governance. The session concludes with a resource sharing activity in which participants identify and evaluate sources of ongoing AI literacy education, fostering habits of self-directed learning.

3.4 Facilitation Model and Librarian Capacity Development

Library professionals serve as facilitators rather than subject-matter experts in the proposed model. This distinction is pedagogically important and practically enabling: it reduces barriers to program adoption by eliminating the requirement for deep technical AI expertise among library staff, while foregrounding the facilitation competencies that librarians already possess.

Prior to program delivery, participating librarians complete a twelve-hour preparation program covering: foundational AI concepts sufficient for confident facilitation; the inquiry-based and problem-based pedagogical approaches used in the modules; facilitation techniques for managing complex discussions about AI and society; and familiarity with the AI tools used in Module 3. A community of practice structure – enabling librarians across sites to share experiences, materials, and strategies – supports ongoing professional development and program quality.

3.5 Pilot Implementation Design

The pilot implementation involves three library sites selected to represent different community contexts: a large urban branch library in Sofia; a municipal library in a mid-sized Bulgarian city (approximately 50,000 inhabitants); and a small community library (chitalishte) in a rural settlement. This selection tests the model's applicability across diverse contexts and populations.

Approximately 60 participants are recruited through library communication channels, community organizations, and local media, with deliberate outreach to populations with lower AI literacy indicators – older adults, individuals with lower formal educational attainment, and residents of areas with limited access to formal digital education. Participation is voluntary and free of charge.

All participants complete a pre-program and post-program assessment using the same instrument, enabling within-subject comparison of knowledge and attitude change. The assessment instrument combines an adapted version of the Meta AI Literacy Scale (MAILS) for self-assessed AI competence, the General Attitudes towards Artificial Intelligence Scale (GAAIS) for attitude measurement, and a facilitator-designed knowledge test targeting the specific conceptual content of the program modules. These instruments have been validated in the Bulgarian context [9], providing psychometrically sound measurement.

4. Evaluation Framework and Indicators

4.1 Evaluation Design

The evaluation uses a mixed-methods pre-post design. Quantitative data from assessment instruments are complemented by qualitative data from structured observation during sessions, facilitator reflective journals, and semi-structured exit interviews with a purposive sample of 15–20 participants across sites. The evaluation addresses three dimensions: learning outcomes (knowledge and skills), attitudinal change, and program quality and feasibility.

4.2 Quantitative Indicators

The primary quantitative indicators are:

- Knowledge gain: change in scores on the facilitator-designed knowledge test from pre- to post-program assessment; target: statistically significant improvement with medium effect size (Cohen's $d \geq 0.5$);
- AI literacy self-efficacy: change in MAILS subscale scores from pre- to post-program; target: positive change across all subscales, with the largest gains expected on competencies directly addressed by program content;
- Attitude change: change in GAAIS scores from pre- to post-program; expected direction: increase in positive/informed attitudes, decrease in fear-based negative attitudes, and maintenance or increase in critical/cautious attitudes;
- Engagement: participation rate (proportion of enrolled participants completing all five modules), session attendance, and active participation indicators;
- Facilitator confidence: pre-post change in librarian self-assessed confidence for AI facilitation.

4.3 Qualitative Indicators

Qualitative indicators include:

- Depth of conceptual understanding: evidence from interviews and observation of participants' ability to apply algorithmic literacy concepts to novel examples beyond program content;
- Attitudinal nuance: evidence of movement from binary attitudes (AI is good/bad) toward more differentiated, context-sensitive evaluations;
- Agency orientation: evidence that participants identify specific actions they can take in relation to algorithmic systems;
- Facilitator experience: evidence from reflective journals of facilitators' perceived confidence, challenges encountered, and suggestions for program improvement;
- Contextual variation: comparison of outcomes across three site types to identify context-specific factors influencing program effectiveness.

4.4 Framework for Assessing Equity Impact

Given the explicit equity orientation of the model, the evaluation also examines differential outcomes across demographic subgroups including age, gender, educational level, and prior digital experience. Pre-program assessment data enable analysis of whether participants from groups with historically lower AI literacy indicators demonstrate comparable learning gains to those with higher baseline competence, which would indicate that the program successfully reduces rather than reproduces existing inequalities.

5. Expected Outcomes and Discussion

5.1 Learning Outcomes

Based on the theoretical framework, the documented efficacy of inquiry-based STEM education in non-formal settings, and evidence from comparable library-based programs, the model is expected to produce significant gains in algorithmic literacy knowledge and self-assessed competence. The IBL structure of Module 3 in particular – in which participants conduct hypothesis-driven experiments with AI tools – is expected to generate strong learning gains on competencies related to understanding AI system behavior, which are often poorly addressed by more didactic approaches.
Evidence from the WebJunction (2025) survey of library AI literacy programs [15] suggests that programs combining theoretical content with hands-on tool exploration and critical discussion produce stronger outcomes than either approach alone. The five-module structure of the proposed model is designed to capitalize on this synergy.

5.2 Attitudinal Change

The expected pattern of attitudinal change reflects the model's emphasis on critical engagement rather than either enthusiasm or alarmism. Participants are expected to report reduced AI anxiety (specifically fear rooted in unfamiliarity or misunderstanding) while maintaining or increasing concern about bias, transparency, and accountability – attitudinal changes that reflect more informed rather than simply more positive orientations toward AI.

This pattern is consistent with findings from comparable non-formal AI education interventions [4], which report that education tends to reduce extreme attitudes in both directions – decreasing both uncritical enthusiasm and technophobic rejection – while increasing the nuance and differentiation of participants' AI-related views.

5.3 Libraries as STEM Infrastructure

The pilot implementation design tests the hypothesis that libraries can function as effective, decentralized STEM learning infrastructure for algorithmic literacy. The multi-site design, spanning urban, peri-urban, and rural contexts, is designed to generate evidence about the boundary conditions of this hypothesis – specifically, whether the model performs comparably across contexts that differ substantially in participant demographics, library resources, and community characteristics.
If the pilot produces the expected outcomes across sites, it would provide empirical support for the policy proposition that libraries should be explicitly incorporated into national STEM education strategies and AI literacy initiatives. This is a claim that IFLA has advanced at the policy level [8, 14], but for which empirical evidence in the European context remains limited.

5.4 Limitations

Several limitations of the proposed study design merit acknowledgment. The absence of a control group prevents causal inference about the effects of program participation; observed pre-post changes may reflect maturation, testing effects, or historical events rather than program impact. The voluntary participation design introduces self-selection bias, potentially overrepresenting citizens already motivated to learn about AI. The twelve-hour librarian preparation program may be insufficient to support high-quality delivery of the more technically complex modules, particularly Module 3, in library contexts with limited technology resources.
Future research should address these limitations through randomized or quasi-experimental designs, extended longitudinal follow-up, and systematic investigation of implementation fidelity and program adaptation across diverse library contexts.

6. Conclusion

This article has proposed a community-based STEM education model for algorithmic literacy implemented within public library settings. Grounded in the theoretical frameworks of inquiry-based learning, non-formal STEM education, and established AI literacy competency frameworks, the model represents a purpose-designed instructional framework for developing citizens' capacity to understand, critically evaluate, and engage with algorithmic systems.
The model's central claims are that: algorithmic literacy is a STEM competence requiring scientific reasoning, data literacy, and inquiry skills; that public libraries are structurally well-positioned to deliver STEM-oriented algorithmic literacy education to populations underserved by formal educational institutions; and that library professionals can serve as effective facilitators of this education with appropriate preparation.
The proposed pilot implementation design provides a rigorous and practically feasible framework for empirically testing these claims. The competency mapping, learning objectives, and evaluation indicators presented here offer a replicable template that can be adapted for library systems operating in different national contexts and with diverse community populations.
In a broader perspective, the model contributes to an emerging understanding of public libraries as decentralized STEM learning hubs – institutions capable of extending science education beyond formal school environments and contributing to more equitable access to AI-related knowledge. At a moment when the algorithmic systems shaping knowledge production, information access, and civic participation are becoming simultaneously more powerful and more consequential, the educational role of public libraries in supporting algorithmic literacy is not a peripheral concern but a central challenge for both library science and science education research.

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