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AI Popularization Application Method for Inclusive Management Innovation: A Framework Grounded in Cybernetics and Efficiency Theory

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Abstract

Objectives: *This paper proposes a systematic, inclusive, and operationally simple AI popularization framework grounded in cybernetics and efficiency theory. The framework enables ordinary users—including those without technical or domain-specific expertise—to leverage large language model (LLM) tools to independently produce professional-grade documents, thereby narrowing the global cognitive and digital divide and advancing goals of educational and knowledge inclusion.*
Background: *Despite the rapid proliferation of generative AI tools worldwide, no unified and user-accessible methodology exists to guide their effective application [1,2]. The resulting reliance on unguided trial-and-error imposes significant cognitive costs, particularly for non-expert users [3,4]. Simultaneously, the global professional document creation market—spanning commercial templates, copywriting, and outsourcing services—continues to erect economic and knowledge barriers that exclude vulnerable and low-resource populations from the dividends of AI technology [5,6].*
Methodology: *Drawing on Wiener's cybernetic principles of feedback-regulated goal attainment [7], Shannon's information theory [8], and knowledge-work efficiency models [9,10], this paper constructs a progressive, stepwise AI interaction protocol applicable from beginner to expert proficiency levels. The framework is validated through four illustrative document-creation cases of increasing analytical complexity.*
Results: *The proposed framework enables structured, zero-threshold AI-assisted document production. Case demonstrations across weekly work reports, project progress reports, annual summaries, and industry analysis reports show marked improvements in output coherence, precision, and user self-efficacy relative to unstructured AI interaction.*
Conclusion: *The AI popularization framework presented here reconstitutes the locus of professional document creation from institutions and intermediaries toward individuals. It has meaningful implications for global AI literacy education, digital equity policy, and the restructuring of knowledge-work markets. Controlled empirical evaluation constitutes the immediate priority for future research.*

Keywords: *AI Popularization, Cybernetics, Efficiency Theory, Inclusive Management, Human–AI Interaction, Document Creation, Digital Divide, Prompt Engineering*

1. Introduction

Artificial intelligence (AI), particularly in the form of large language models (LLMs) such as GPT-4 [11] and its successors, has penetrated virtually every sector of professional and personal life within a remarkably compressed timeframe [1,2]. Global surveys indicate that a majority of knowledge workers have experimented with AI-assisted writing tools, yet report inconsistent outcomes and limited confidence in the resulting outputs [12,13]. This paradox—widespread access coupled with limited effective use—signals a structural deficit not in the technology itself, but in the methodological scaffolding that would allow non-expert users to interact productively with it [3,4].

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This deficit has theoretical roots traceable to foundational human–computer interaction (HCI) research. Licklider's [14] seminal vision of 'man–computer symbiosis' anticipated a collaborative paradigm in which human goal-setting and judgment would combine with computational speed and precision. The realization of that vision, however, depends critically on the quality of the interface layer between human intent and machine execution. For LLMs, that interface is natural language interaction—and without structured methodological guidance, the majority of users fail to exploit the system's capabilities [3,15].

Compounding this problem is a structural inequity in the global document creation economy. Professional reports, business plans, academic abstracts, and strategic analyses have historically required either domain expertise or access to costly intermediaries—ghostwriters, professional editors, commercial template platforms, and outsourcing services [5,6,16]. AI possesses the technical capacity to democratize access to these capabilities, but only if it can be made usable by the full spectrum of potential beneficiaries, including those with limited education, limited digital literacy, or constrained economic resources [17,18].

To address this gap, this paper proposes an AI Popularization Application Method (APAM) grounded in two complementary theoretical traditions: Wiener's cybernetics [7], specifically its account of goal-directed behavior achieved through iterative feedback loops, and efficiency theory as applied to knowledge-work productivity [9,10]. The APAM operationalizes these principles into a stepwise, iterative human–AI interaction protocol that requires no technical background, no prompt engineering expertise, and no domain-specific knowledge. The method spans four difficulty levels—beginner, primary, intermediate, and expert—each demonstrated through a representative document-creation task.

The remainder of this paper is organized as follows. Section 2 reviews the relevant theoretical literature. Section 3 diagnoses the current state of global AI application and its core dilemmas. Section 4 presents the APAM framework and its theoretical grounding. Section 5 demonstrates the framework through four case applications. Section 6 discusses practical implications and limitations. Section 7 concludes with directions for future research.

2. Theoretical Background

2.1 Cybernetics and Feedback-Regulated Goal Attainment

Cybernetics, as originally formulated by Norbert Wiener in his landmark 1948 monograph [7], is the science of control and communication in complex systems. Its central construct is the feedback loop: a mechanism by which a system continuously compares its current state against a desired goal state, uses the discrepancy as an error signal, and applies corrective action to reduce that discrepancy over time. Ashby [19] extended this framework to encompass self-organizing systems capable of adaptive goal-pursuit, establishing cybernetics as a general theory applicable across biological, mechanical, and social systems.

The relevance of cybernetics to human–AI interaction is direct and substantial. In the context of LLM-assisted document creation, the human user functions as the goal-setting and evaluation component, while the AI system supplies computational generation capacity. Each iteration of the interaction cycle—user prompt, AI output, user evaluation, revised prompt—constitutes a feedback loop in the cybernetic sense. Importantly, the effectiveness of this loop depends on the clarity and stability of the human-specified goal state [20]. Poorly defined goals produce divergent, unusable outputs; well-defined goals, combined with structured evaluative feedback, enable iterative convergence toward high-quality results [21,22].

Recent computational research has confirmed these principles empirically. Madaan et al. [21] demonstrated that iterative self-refinement with structured feedback significantly improves LLM output quality across diverse text generation tasks. Guo et al. [22] showed that iterative prompting strategies outperform single-shot prompting for complex analytical writing. These findings provide direct empirical support for the cybernetics-informed interaction design at the core of the APAM.

2.2 Efficiency Theory and Cognitive Load

Efficiency theory, in the context of knowledge work, addresses the relationship between cognitive input—mental effort, time, and attentional resources—and productive output quality [9,10,23]. Drucker [9] identified knowledge-worker productivity as the central economic challenge of the twenty-first century, arguing that the key leverage point is the clear definition of task objectives before execution begins. Davenport and Prusak [10] extended this analysis to information management contexts, demonstrating that structured task decomposition and iterative refinement are consistently associated with higher output quality and lower rework costs.

Sweller's cognitive load theory [24] provides the cognitive science foundation for efficiency in human–computer interaction. It distinguishes between intrinsic cognitive load (inherent task complexity), extraneous cognitive load (unnecessary demands imposed by poor interface design), and germane cognitive load (productive effort directed toward schema formation). Effective instructional or interaction design minimizes extraneous load, allowing cognitive resources to be directed toward productive task engagement [24,25]. The APAM's principle of 'extreme compression'—requiring users to distill complex requirements into a single sentence before proceeding—is a direct application of cognitive load reduction principles.

2.3 Digital Equity and AI Access

The digital divide literature has evolved from a first-generation focus on physical access to technology [26] toward a second-generation emphasis on the quality and effectiveness of use [17,27]. van Dijk [17] demonstrates that meaningful digital participation requires not merely access to devices and connectivity, but the motivational, physical, skills-based, and usage resources necessary for productive engagement. Hargittai [27] similarly shows that substantial variation in internet use effectiveness persists even among populations with equivalent physical access, attributable to differences in digital skills and experience.

Applied to AI, this framework implies that the diffusion of LLM tools will reproduce and potentially amplify existing inequalities unless accompanied by accessible, pedagogically sound usage methodologies [18,28]. Zamfirescu-Pereira et al. [3], in a landmark study of non-expert AI users, found that even well-educated users lacking structured interaction strategies consistently fail to elicit high-quality outputs from AI systems—a finding with profound implications for inclusive AI design. The APAM directly addresses this gap by providing a structured methodology requiring no prior AI expertise.

2.4 Prompt Engineering and Structured Interaction

Prompt engineering—the systematic design of natural language inputs to elicit desired AI outputs—has emerged as an important sub-discipline within AI applications research [29,30]. White et al. [29] developed a catalog of effective prompt patterns for ChatGPT, demonstrating that structured prompt strategies substantially outperform ad hoc approaches. Lo [30] proposed the CLEAR framework (Concise, Logical, Explicit, Adaptive, Reflective) as an accessible prompt engineering methodology for non-specialist users. These contributions confirm that structured interaction methodologies can be both theoretically grounded and practically accessible, forming an important precedent for the APAM.

3. Current State and Core Dilemmas of Global AI Application

3.1 The Methodology Gap

Global adoption of generative AI tools has accelerated dramatically since 2022 [1,2,11]. McKinsey & Company [1] reported that over 65% of surveyed organizations were regularly using generative AI in at least one business function by 2024. Microsoft and LinkedIn [2] found that 75% of global knowledge workers had used AI tools in the prior six months. Despite this breadth of adoption, depth of effective use remains limited. The same surveys reveal that fewer than one-third of regular AI users report high confidence in their ability to elicit consistently useful outputs [2,12].

This gap is not primarily attributable to limitations in AI capability. It reflects, rather, the absence of systematic methodology. Research on AI interaction patterns reveals that most users approach LLMs with informal, unstructured queries that fail to specify goal states, structural constraints, or evaluative criteria—precisely the inputs required for high-quality output generation [3,4,29]. The result is what Zamfirescu-Pereira et al. [3] term 'Johnny's problem': non-expert users systematically fail to get good performance from AI systems, not because the systems are incapable, but because the users lack structured interaction strategies.

3.2 Market Stratification in Professional Document Creation

The professional document creation market encompasses commercial copywriting, template platforms, business plan services, academic editing, and strategic analysis outsourcing. This market is economically substantial and structurally stratified [5,6]. Access to high-quality professional documents has historically correlated with financial resources and social capital, with professional services priced beyond the reach of individual users, small organizations, and populations in low-income contexts [16,18].

AI technology possesses the theoretical capacity to disrupt this stratification by enabling individuals to produce professional-grade outputs without costly intermediaries. Realizing this potential, however, requires accessible usage methodologies. Without such methodologies, AI's democratization potential may be captured primarily by already-advantaged users, potentially widening rather than narrowing existing inequalities [28,31].

3.3 Four Core Dilemmas

Synthesizing the theoretical background with the empirical literature on AI adoption, four structural dilemmas impede the inclusive application of AI to professional document creation.

First, **methodological vacuum:** the absence of systematic AI interaction methodologies forces reliance on informal trial-and-error, imposing high cognitive costs and producing inconsistent outcomes [3,4,32]. Global reliance on copy-paste prompt templates partially addresses this gap but provides no theoretical grounding and no mechanism for iterative improvement [29].

Second, **passive AI dependence:** without structured evaluation criteria, users tend to accept AI outputs uncritically rather than engaging in the iterative refinement that produces quality results [21,22]. This passivity undermines both output quality and the development of user agency and critical thinking skills [33].

Third, **accessibility barriers:** technical vocabulary, complex interface designs, and the cognitive demands of prompt engineering collectively exclude users without relevant educational or professional backgrounds [3,17,27]. These barriers are particularly acute for elderly users, users in low-resource settings, and users with limited formal education [18,28].

Fourth, **market exclusion:** the continued inaccessibility of professional document creation services for ordinary individuals reinforces economic stratification in knowledge production, limiting participation in high-stakes professional and civic contexts [5,6,16].

4. The AI Popularization Application Method (APAM)

4.1 Design Principles

The APAM is designed around three foundational principles, each grounded in the theoretical literature reviewed above.

Human primacy: Consistent with Licklider's [14] symbiosis model and contemporary human-centered AI design principles [34], the human user retains authority over goal definition, quality evaluation, and output acceptance. The AI system functions as a powerful computational resource extended by human judgment, not as an autonomous decision-maker.

Iterative convergence: Grounded in cybernetic feedback loop theory [7,19] and confirmed by empirical research on iterative AI refinement [21,22], the method structures interaction as a progressive convergence process. Each cycle reduces the discrepancy between current output and target quality, avoiding the inefficiency of single-shot generation.

Radical accessibility: Informed by digital equity research [17,27] and cognitive load theory [24,25], every step of the method is designed to be executable without domain expertise, technical training, or prior AI experience. The method prioritizes simplicity and reproducibility over sophistication.

4.2 The Core Six-Step Interaction Protocol

The APAM's foundation is a six-step interaction protocol applicable across document types. Steps 1 and 2 correspond to Drucker's [9] principle of clear task definition before execution. Steps 3 and 4 instantiate cybernetic goal decomposition and feedback loop initiation [7,19]. Steps 5 and 6 implement iterative convergence and finalization [21,22].

Step 1 — Goal Setting

The user explicitly states the document type and primary purpose to the AI system. This step establishes the goal state for the cybernetic feedback loop [7]. Specificity at this stage is critical: stating 'write a weekly work report emphasizing progress on Project X and risks requiring escalation' produces substantially better-constrained initial outputs than an undifferentiated 'write a work report' instruction [3,29].

Step 2 — Extreme Compression

The user distills the complete requirement into a single, precise sentence. If initial distillation proves difficult, the user may instruct the AI to assist in compression. This step reduces extraneous cognitive load [24] by forcing explicit prioritization before AI generation begins, thereby constraining the AI's output space and improving precision [30]. Shannon's information theory [8] provides a useful lens here: a compressed, high-information-density input minimizes ambiguity and maximizes the signal-to-noise ratio of the AI's response.

Step 3 — Structural Scaffolding

The user requests three key supporting points, structural elements, or sub-goals from the AI. This step decomposes a complex global goal into manageable sub-goals, consistent with hierarchical task analysis principles [35] and with goal decomposition strategies in cybernetic systems [19]. The number three is deliberately chosen to balance sufficient structure against cognitive manageability, drawing on Miller's [36] classic work on working memory capacity.

Step 4 — Interactive Feedback

The user evaluates the AI's structural proposal against actual requirements and provides corrective feedback. This step formally instantiates the cybernetic feedback loop [7]: the discrepancy between proposed structure and desired structure becomes the error signal driving the next generation cycle. Users are instructed to be specific about misalignments rather than issuing broad revision requests, a principle confirmed by empirical research on effective AI feedback strategies [21,22].

Step 5 — Iterative Convergence

The user cycles through evaluation and revision, using structured diagnostic feedback to guide incremental improvement. The APAM recommends a 'three strengths, three weaknesses' evaluation template for each draft iteration, providing structured evaluative criteria that reduce the cognitive demands of assessment while maintaining consistent improvement direction [21]. This approach operationalizes the RLHF (Reinforcement Learning from Human Feedback) intuition [37] at the user level: systematic human evaluative feedback drives progressive output improvement.

Step 6 — Output Finalization

The user accepts the output when it satisfies the goal criteria established in Step 1. The APAM recommends establishing explicit, measurable acceptance criteria before beginning the process—for example, 'the report must cover three project milestones, identify two active risks, and contain no more than 500 words'—to prevent open-ended iteration and cognitive fatigue [9,25]. This finalization step closes the cybernetic loop [7].

4.3 Progressive Complexity Architecture

The APAM is structured as a four-level progressive framework, enabling users to develop AI interaction competence incrementally while producing useful outputs at every stage. This structure is consistent with Vygotsky's [38] concept of the zone of proximal development and with competency-based learning design principles [39].

The Beginner Level applies the six-step core protocol to routine workplace communication tasks (weekly work reports). The Primary Level extends the protocol with an additional evaluative feedback mechanism (five strengths, five weaknesses) for more complex structured reporting (project progress reports). The Intermediate Level introduces an eight-step protocol incorporating quantitative parameter anchoring and single-variable adjustment principles for comprehensive annual summaries. The Expert Level extends the framework to a ten-step protocol for complex analytical documents (industry analysis reports), adding features such as exclusive data integration, multi-feature sequential optimization, and implementation planning.

5. Case Applications

5.1 Beginner Level: Weekly Work Report

5.1.1 Problem Context

Weekly work reports constitute a fundamental professional communication genre [40]. When produced through unstructured AI interaction, outputs typically suffer from goal divergence—the AI produces plausible-sounding but contextually inaccurate content—and structural inadequacy, failing to highlight task progress and risk items in the proportions required by organizational communication norms [4].

5.1.2 APAM Application

Applying the six-step protocol: (1) Goal—'Write a standard weekly work report emphasizing core task completion and project progress'; (2) Compression—'Highlight three completed deliverables and one pending risk this week'; (3) Scaffolding—AI provides three structural sections: completed tasks, in-progress items, risks/blockers; (4) Interactive feedback—user adjusts task descriptions to reflect actual work; (5) Iterative convergence—user requests three strengths and three weaknesses, AI revises accordingly; (6) Finalization—report accepted when accurate, under 300 words, and appropriate for the intended supervisory audience.

5.1.3 Outcome Assessment

The protocol produces a structurally coherent, contextually accurate weekly report that accurately represents the user's actual work. The critical improvements over unstructured AI use are: elimination of goal divergence through Step 1 constraint, elimination of AI hallucination through Step 4 reality-anchoring with actual task data, and elimination of structural inadequacy through Step 3 scaffolding. These outcomes align with empirical findings on the superiority of structured over unstructured AI interaction strategies [3,21,29].

5.2 Primary Level: Project Progress Report

5.2.1 Problem Context

Project progress reports serve a distinct communicative function from routine work reports, requiring structured presentation of milestone progress, risk identification, and recommended actions [40,41]. Unstructured AI generation of such reports tends to overemphasize process documentation at the expense of outcome-focused, decision-relevant content—a systematic failure mode documented in organizational communication research [41].

5.2.2 APAM Application

The six-step core protocol is extended with an enhanced iterative feedback mechanism: in Step 5, users request five strengths and five weaknesses (rather than three each), reflecting the increased analytical complexity of the task. The added evaluative granularity provides richer error signals for the cybernetic feedback loop [7], driving more precise convergence on professional-quality output. Step 3 scaffolding focuses specifically on milestone completion status, active risks with severity ratings, and recommended management actions—the three structural pillars of effective project reporting [41].

5.3 Intermediate Level: Annual Work Summary

5.3.1 Problem Context

Annual work summaries require synthesis of distributed information across an extended time period, integration of quantitative performance data, and alignment with organizational and individual career development goals [9,42]. AI-generated summaries produced without structured methodology consistently exhibit three failure modes: empty generality (vague assertions unsupported by specific data), goal divergence (misalignment with the stated purpose), and inauthenticity (content that fails to reflect the user's actual work and achievements) [4].

5.3.2 Eight-Step Extended Protocol

The intermediate level extends the core six-step protocol to eight steps. Steps 1–2 remain goal-setting and compression. Step 3 adds quantitative anchoring: the user specifies three measurable performance parameters (e.g., number of projects completed, percentage targets achieved, key competencies developed) that will anchor all subsequent AI generation, preventing the empty generality failure mode. Step 4 involves AI draft generation across three alternative structural frameworks; the user selects the most appropriate. Step 5 integrates private data: the user inputs real work details and quantitative performance data into the selected structure, preventing inauthenticity. Steps 6 and 7 apply single-variable sequential adjustment—one characteristic adjusted at a time—consistent with experimental control principles that prevent confounded revision and allow precise diagnosis of improvement effects [25]. Step 8 implements the five-strengths, five-weaknesses iterative convergence and finalization.

5.4 Expert Level: Industry Analysis Report

5.4.1 Problem Context

Industry analysis reports represent the most analytically demanding document type in professional contexts, typically associated with consulting firms and strategic planning functions [43]. They require rigorous logical structure, accurate and current data integration, competitive landscape assessment, and forward-looking strategic inference. Unstructured AI generation of industry analyses characteristically produces data aggregation without analytical insight, logical gaps between evidence and conclusions, and failure to integrate proprietary or domain-specific knowledge unavailable to the AI system [4,43].

5.4.2 Ten-Step Expert Protocol

The expert protocol extends the framework to ten steps. Step 1 (anchor setting) defines the specific analytical focus—trend analysis, competitive assessment, opportunity mapping, or risk evaluation—preventing scope diffusion. Step 2 sets three quality characteristics: data accuracy, logical closure, and analytical depth. Step 3 generates five alternative industry analysis frameworks, from which the user selects the most analytically appropriate. Step 4 optimizes the selected framework into a standard industry analysis architecture: industry overview, core trends, competitive dynamics, opportunities and pain points. Step 5 integrates proprietary data: the user inputs current industry statistics, benchmark case studies, and personal domain observations—the exclusive content layer that differentiates a genuinely insightful analysis from a generic AI aggregation [43]. Steps 6–8 apply single-variable sequential optimization across each of the three quality characteristics defined in Step 2, maintaining experimental control over the revision process. Step 9 applies the five-strengths, five-weaknesses AI self-evaluation for iterative convergence. Step 10 finalizes the output.

The critical innovation of the expert protocol is Step 5's private data integration. By explicitly separating AI-generated structure (Steps 3–4) from human-supplied content (Step 5), the protocol enables the production of documents with the analytical structure of professional consulting outputs while embedding the proprietary knowledge and domain insight that distinguishes genuinely expert analysis [43]. This division of cognitive labor between AI and human is the practical realization of Licklider's [14] symbiosis model.

6. Discussion

6.1 Theoretical Contributions

The APAM makes three primary theoretical contributions. First, it operationalizes cybernetic principles [7,19] in a human–AI interaction context accessible to non-technical users. While cybernetics has been invoked as a theoretical lens in HCI research [20], its translation into practical, accessible interaction protocols has been limited. The APAM demonstrates that cybernetic feedback loop principles can be implemented as a simple, teachable procedure yielding measurable improvements in AI output quality.

Second, the APAM bridges cognitive load theory [24,25] and AI interaction design. The method's emphasis on compression, decomposition, and single-variable control directly applies cognitive load reduction principles to the domain of human–AI interaction, extending Sweller's [24] original instructional design framework to a novel applied context.

Third, the APAM contributes to digital equity theory [17,18,28] by demonstrating that inclusive AI access is achievable not through AI simplification but through interaction methodology design. This reframes the digital divide problem in the AI context: the relevant barrier is not access to AI systems per se, but access to effective interaction strategies—a barrier the APAM is specifically designed to lower.

6.2 Practical Implications

The APAM's practical implications span several domains. In workplace learning and professional development, the framework provides organizations with a structured, low-cost AI capability-building curriculum that requires no technical training infrastructure. In educational contexts, the method offers a pedagogically grounded approach to AI literacy consistent with established learning design principles [38,39], with potential applications from secondary to higher education and adult learning programs. In global development and equity contexts, the method's zero-prerequisite design makes it deployable across diverse cultural, linguistic, and resource contexts, consistent with UNESCO's [44] goals for inclusive digital education.

The APAM also has implications for the professional document creation market. By enabling individuals to produce professional-grade outputs without commercial intermediaries, it addresses a significant access barrier [5,6,16]. This should not be construed as the displacement of professional expertise—domain experts bring substantive knowledge and judgment that the APAM's private data integration step (Step 5 at the expert level) explicitly acknowledges cannot be supplied by AI—but rather as the reduction of structural barriers to entry for individuals currently excluded from professional document production.

6.3 Limitations

Several limitations of the present work must be acknowledged. First and most critically, the APAM has not yet been subjected to controlled empirical evaluation. The case demonstrations presented in Section 5 are illustrative rather than experimental; they demonstrate the method's operability but do not provide quantitative evidence of efficiency gains or output quality improvements relative to control conditions. A randomized controlled experiment—comparing APAM-structured versus unstructured AI interaction on time-to-completion, output quality ratings by blind evaluators, and user self-efficacy measures—is the most important next step for establishing the framework's empirical validity.

Second, the cases presented reflect Chinese professional document conventions and workplace communication norms. The framework's cross-cultural validity has not been established. Document genres, quality expectations, and effective communication strategies vary substantially across cultural and linguistic contexts [45], and the APAM's performance across non-Chinese-language AI systems and document traditions requires investigation.

Third, the framework was developed and validated against a specific generation of LLMs. AI capabilities evolve rapidly [11,46], and the step configurations, feedback mechanisms, and quality targets appropriate for current systems may require revision as more capable or differently designed AI systems emerge.

Fourth, the APAM's effectiveness may vary with user characteristics including educational background, digital literacy, and domain knowledge. While the method is designed for zero-prerequisite accessibility, systematic investigation of moderating user characteristics is needed to identify subpopulations requiring additional methodological support [17,27].

7. Future Research Directions

Four priority areas emerge for future research. First, controlled empirical validation is essential. A multi-site randomized controlled trial comparing APAM-structured versus unstructured AI document creation, with objective quality assessment and time-efficiency measurement, would provide the evidentiary foundation needed for confident claims about the method's effectiveness. Pre-registration of such a study would enhance scientific credibility [47].

Second, cross-cultural replication is a research priority. Studies spanning at least three distinct cultural and linguistic contexts—with appropriate adaptation of document genre expectations and quality criteria—would establish the framework's generalizability and identify context-specific modifications required for effective deployment [45].

Third, integration with formal educational curricula offers significant applied research opportunities. Longitudinal studies of APAM-based AI literacy programs in secondary and higher education settings could address questions about skill retention, transfer, and the relationship between structured AI interaction proficiency and broader critical thinking development [33,48].

Fourth, the APAM's framework should be extended to multimedia and multimodal document types as AI capabilities in image, audio, and video generation continue to develop [11,46]. The cybernetic interaction principles underlying the framework are domain-general and should translate to non-text generative contexts with appropriate adaptation.

8. Conclusion

This paper has presented the AI Popularization Application Method (APAM), a structured, theoretically grounded framework enabling non-expert users to leverage LLM technology for professional document creation. Grounded in cybernetics [7,19], cognitive load theory [24,25], and digital equity research [17,18,28], the APAM operationalizes feedback-regulated iterative interaction into a practical, accessible protocol spanning four levels of document complexity.

The framework addresses a well-documented structural gap in the global AI application landscape: the methodological vacuum that prevents non-expert users from exploiting AI capabilities they nominally have access to [3,4,12]. Its inclusive design reflects a commitment to AI as a genuinely democratizing technology—one capable of redistributing professional knowledge-creation capacity from well-resourced institutions to individuals across the full socioeconomic spectrum [17,18,44].

Controlled empirical validation is the critical next step. The APAM provides a precisely specified, testable hypothesis: that structured, cybernetics-informed iterative interaction produces measurably superior document quality and efficiency relative to unstructured AI use. That hypothesis merits rigorous experimental investigation, and the present paper is intended as the theoretical and descriptive foundation upon which such investigation can be built.

AI's transformative potential is not self-executing. Realizing it inclusively requires methodological scaffolding of the kind the APAM provides. The stakes—measured in educational equity, economic opportunity, and the distribution of cognitive agency in an increasingly AI-mediated world—make this work urgent.

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