

Artificial Intelligence Humanics as an Integrative Framework for Human Outcomes in the Generative Artificial Intelligence Era: A Narrative Review and Conceptual Synthesis

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Received: May 23, 2026 | Review began: May 29, 2026 | Review ended: July 07, 2026 | Published: July 27, 2026

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Abstract

Generative artificial intelligence (AI) is increasingly used in healthcare, education, research, governance, and professional practice. Existing scholarship has advanced human-centered AI, human-AI interaction, AI ethics, AI literacy, sociotechnical systems, responsible AI, and implementation science, but these literatures often emphasize different analytic levels and outcomes. This narrative review and conceptual synthesis propose Artificial Intelligence Humanics (AI Humanics) as an integrative framework for examining human outcomes in AI-mediated practice. A SANRA-informed narrative review approach was used to synthesize literature on human-centered AI, human-AI collaboration, trust and overreliance, AI literacy, AI ethics and governance, AI sociology, professional education, healthcare implementation, research integrity, AI incident learning, and selected regulatory perspectives. An initial candidate matrix of 94 sources was assembled; after two-stage screening and conceptual mapping, 56 sources were retained for the revised synthesis. AI Humanics is defined as a proposed framework for examining how AI-mediated environments can affect human agency, professional expertise, care communication, learning transfer, trust calibration, responsibility, and institutional practice. The framework is not intended to replace human-centered AI, responsible AI, sociotechnical systems research, or implementation science. Its intended contribution is to complement AI capability evaluation with a structured human-outcome perspective. The proposed seven-domain framework comprises human agency, expertise transformation, care and communication, learning transfer, trust calibration, responsibility and accountability, and social implementation fit. The framework remains provisional and requires empirical validation, but it may provide a common language for future research, education, governance, and implementation studies that evaluate not only what AI systems can produce, predict, or automate, but also how AI use affects human capacities, professional roles, and institutional accountability.

Categories: AI and the Future of Peer Review, AI Ethics, AI for Sustainable Development Goals (SDGs)

Keywords: artificial intelligence, generative ai, ai humanics, human-centered ai, human-ai interaction, ai literacy, ai ethics, professional education, sociotechnical systems, implementation science

Introduction And Background

Generative artificial intelligence (AI) has moved from a specialized computational technology into a widely used environment for research, education, healthcare, governance, and professional work. Large language models (LLMs) and related systems are used to draft text, summarize evidence, support decision-making, provide feedback, simulate dialogue, and assist learning. As these tools become embedded in everyday practice, the central question is no longer limited to whether AI systems can perform particular tasks. A parallel question is how AI use affects humans, professions, organizations, and social institutions that adopt it.

How to cite this article:

Harada Y (July 27, 2026) Artificial Intelligence Humanics as an Integrative Framework for Human Outcomes in the Generative Artificial Intelligence Era: A Narrative Review and Conceptual Synthesis. Cureus J AI Augment Res 1 : es44568-026-00185-3. DOI <https://doi.org/10.7759/s44568-026-00185-3>

Existing scholarship has addressed this issue from several directions. Human-centered AI and human-AI interaction research emphasize reliable, safe, trustworthy, understandable, and collaborative systems aligned with human needs and values [1-3]. Research on algorithm aversion, algorithm appreciation, trust, overreliance, automation bias, sense of agency, and human-generative AI collaboration shows that people do not use AI as neutral information; they interpret, defer to, resist, overtrust, undertrust, or become motivationally affected by algorithmic outputs in ways that influence judgment [4-7]. AI literacy and generative AI education research has examined competencies required to understand, evaluate, and responsibly use AI systems in educational and professional settings [8-10]. AI ethics, governance, accountability, auditing, research integrity, and responsible AI scholarship has developed principles and mechanisms for transparency, fairness, accountability, human oversight, evidence verification, and responsible deployment [11-14]. Sociology of AI and sociotechnical systems research has highlighted how AI is embedded in institutions, power relations, labor processes, inequality, data justice, and coloniality [15-17]. Professional education and healthcare implementation research has raised concerns about clinical judgment, deskilling, professional acceptance, governance, translational pathways, and AI education for health professionals [18-21]. AI incident reporting and regulatory studies further show that institutional learning, sectoral coordination, and legal preparedness are important for responsible AI implementation [22-24].

The rationale for AI Humanics is not that these fields ignore human outcomes. Rather, each field tends to foreground different analytic levels. Human-centered AI and human-AI interaction often begin with system design, interaction patterns, and user experience [1-3]. AI literacy often emphasizes competencies, instruction, and assessment [8,9]. AI ethics and responsible AI emphasize principles, governance mechanisms, and accountability instruments [11-13]. Sociotechnical systems and sociology of AI emphasize institutions, power, labor, inequality, and data justice [15-17]. Implementation science emphasizes adoption, workflow integration, and sustainability [20,25,26]. These perspectives are necessary, but they are not always integrated around a shared set of human-outcome domains that can be evaluated across learning, professional practice, communication, accountability, and institutional implementation.

This gap is especially important in the generative AI era. Generative AI systems participate in activities closely connected to professional identity and human practice, including writing, explanation, teaching, research synthesis, clinical communication, decision support, and knowledge work [7,10,14,18,20]. Their effects should not be evaluated only through system-centered metrics such as accuracy, efficiency, usability, or safety. These metrics remain essential, but they are incomplete if they do not also examine whether AI use preserves or weakens human agency, transforms expertise, alters care and communication, supports or undermines learning transfer, calibrates or distorts trust, clarifies or diffuses responsibility, and fits or disrupts social institutions.

This review proposes AI Humanics as an integrative framework for addressing this gap. The term is used here to denote the study of AI-mediated human practice. In this manuscript, AI-mediated human practice refers to human activity in which AI systems participate in information generation, decision support, communication, learning, verification, or organizational processes. It is not a single empirical unit. Depending on the study design, it can be operationalized at individual or professional level, interactional or team level, or institutional or sectoral level. This clarification is important because a learner using an AI tutor, a clinician reviewing AI-assisted documentation, a research team verifying AI-generated citations, and an organization responding to an AI incident all represent different levels of AI-mediated human practice.

AI Humanics is not proposed as a replacement for human-centered AI, responsible AI, AI literacy, AI sociology, sociotechnical systems research, implementation science, or human-factors-oriented engineering. Rather, it is proposed as an integrative layer that connects these adjacent fields around one organizing question: how does AI use affect human agency, expertise, care, learning, trust, responsibility, and social implementation?

The purpose of this narrative review and conceptual synthesis is threefold. First, it synthesizes adjacent bodies of literature relevant to AI-mediated human outcomes. Second, it defines AI Humanics as a proposed integrative framework that is complementary to, rather than separate from or superior to, human-centered AI, responsible AI, sociotechnical

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systems research, and implementation science. Third, it proposes a seven-domain AI Humanics framework and illustrates how the domains can be operationalized for future empirical research. By doing so, this review aims to provide a common conceptual language for educational design, governance, and implementation studies in the generative AI era.

Review

Review approach and conceptual synthesis

This article was designed as a narrative review and conceptual synthesis. This design was selected because the objective was not to estimate a pooled effect size, evaluate a single intervention, or exhaustively map one bounded empirical literature. Rather, the aim was to integrate heterogeneous conceptual, empirical, ethical, educational, sociological, regulatory, and implementation-oriented literatures into a coherent framework for studying human outcomes in AI-mediated practice. The review design was informed by SANRA, a scale for the quality assessment of narrative review articles, and by established typologies distinguishing narrative reviews from systematic reviews, scoping reviews, conceptual reviews, and meta-analyses [27,28].

The guiding review question was as follows: how can scholarship on human-centered AI, human-AI interaction, AI literacy, AI ethics and governance, sociology of AI, sociotechnical systems, professional education, healthcare implementation, expertise transformation, incident learning, and regulatory readiness be integrated into a framework for studying human outcomes in AI-mediated practice?

A purposive and iterative search strategy was used to identify literature relevant to AI-mediated human outcomes. Searches were conducted across PubMed/MEDLINE, Scopus, Web of Science, ACM Digital Library, IEEE Xplore, ScienceDirect, Google Scholar, and publisher databases. The search was updated in May 2026, and a targeted update was conducted during revision to address governance, incident learning, and regulatory perspectives. Additional sources were identified through backward and forward citation tracking from highly relevant review articles, conceptual papers, and governance documents.

Search terms were combined iteratively rather than applied as a single rigid Boolean string because the review spanned multiple disciplines. Core search concepts included human-centered AI, human-AI interaction, human-AI collaboration, human-in-the-loop AI, AI trust, trust calibration, algorithm aversion, algorithm appreciation, automation bias, sense of agency, AI literacy, artificial intelligence literacy, generative AI education, AI ethics, AI governance, trustworthy AI, algorithmic accountability, AI auditing, model cards, datasheets for datasets, sociotechnical AI, sociology of artificial intelligence, AI and social inequality, AI and professional expertise, AI-induced deskilling, LLMs in medical education, generative AI in healthcare, AI implementation, implementation science artificial intelligence, AI incidents, organizational learning from AI failures, sector-led AI governance, and AI regulation in telecommunications. Example search combinations included human-centered AI AND human-AI interaction, AI literacy AND generative AI education, trust calibration AND human-AI interaction, automation bias AND healthcare AI, AI governance AND accountability, sociotechnical AI AND inequality, generative AI AND medical education, AI incidents AND organizational learning, and AI regulation AND sector governance.

The search prioritized literature published from 2015 onward because this period captures the rapid expansion of modern AI ethics, human-centered AI, human-AI interaction, AI literacy, and applied generative AI research. Foundational earlier studies were included when they were necessary to define key concepts such as automation bias, algorithm aversion, human-centered design, or review methodology. Recent studies from 2024 to 2026 were prioritized when they addressed generative AI, professional practice, medical or health professional education, research integrity, AI literacy, healthcare implementation, governance coordination, or regulatory readiness.

Sources were eligible for inclusion when they met at least one of the following criteria: they addressed human-centered AI or human-AI collaboration; examined human agency, trust, overreliance, automation bias, or sense of agency; defined or evaluated AI literacy, AI learning, or generative AI education; discussed AI ethics, governance, accountability, auditing, or research integrity; analyzed AI as a sociological or sociotechnical phenomenon; examined professional expertise,

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healthcare education, care, or communication; addressed implementation science and organizational adoption of AI; discussed AI incident reporting or organizational learning from AI failures; or examined legal, regulatory, or sector-specific governance environments relevant to AI implementation. Peer-reviewed articles, systematic reviews, scoping reviews, narrative reviews, conceptual articles, influential institutional guidelines, and selected preprints suggested during peer review were considered eligible.

Sources were excluded or deprioritized when they focused narrowly on technical model architecture, benchmark performance, optimization, or engineering without addressing human use, professional practice, education, governance, ethics, care, accountability, regulation, or implementation. Duplicate records, non-English sources, non-scholarly commentaries without clear conceptual relevance, sources that substantially overlapped with more comprehensive reviews, and sources that did not contribute to the proposed conceptual domains were also excluded or deprioritized.

The selection process was conducted in two stages. First, titles, abstracts, and source types were screened for relevance to the review question and to at least one conceptual domain. Second, full texts or full guideline documents were reviewed for conceptual relevance, methodological importance, and contribution to one or more proposed AI Humanics domains. An initial candidate matrix of 94 sources was assembled. Of these, 52 sources were selected for the first revised manuscript, and 42 were reserved or excluded because they were technically narrow, substantially overlapping, less central to the framework, or outside the intended scope. During peer-review revision, four additional sources were added to address AI incidents, sector-led governance, cross-jurisdictional regulatory preparedness, and formal legal regulation, yielding a final reference set of 56 sources.

Conceptual mapping was conducted manually using a matrix that recorded each source's disciplinary domain, article type, core concept, target setting, relevance to AI-mediated human outcomes, and relation to candidate domains. The framework-development process was not a formal grounded-theory study, expert Delphi process, or systematic thematic synthesis. To reduce subjectivity, a candidate domain was retained only when it satisfied three conditions: it appeared across at least two adjacent literature clusters; it referred to a human outcome or practice rather than only to a technical system property; and it could plausibly be operationalized through future empirical indicators. This process produced seven domains: human agency, expertise transformation, care and communication, learning transfer, trust calibration, responsibility and accountability, and social implementation fit.

Because this was a narrative review and conceptual synthesis rather than a systematic review, no formal PRISMA flow diagram, risk-of-bias assessment, or exhaustive search log was prepared. This limits reproducibility and is acknowledged as a limitation. The purpose of the method was theory-building and conceptual integration, not exhaustive evidence retrieval or effect estimation.

Human-centered AI and Human-AI collaboration

Human-centered AI provides an important starting point for AI Humanics. This field emphasizes that AI systems should be reliable, safe, trustworthy, understandable, and aligned with human values and needs. Shneiderman's work argues for systems that combine high levels of automation with meaningful human control, thereby avoiding a false dichotomy between human authority and machine autonomy [2]. Xu's human-computer interaction perspective frames human-centered AI as a design orientation in which intelligent systems should augment rather than replace human capacities [29].

Human-AI interaction research has translated these principles into practical design guidance. Amershi et al. proposed guidelines that address how systems should communicate uncertainty, support user correction, enable feedback, and manage expectations across the interaction lifecycle [1]. More recent reviews and taxonomies suggest that collaboration remains uneven, with many AI-assisted systems functioning primarily as recommendation tools rather than as genuinely reciprocal collaborators [3,30].

For AI Humanics, this literature makes an essential contribution by establishing that AI evaluation must account for human goals, values, interaction contexts, and collaboration quality. AI Humanics adds a complementary temporal and outcome-oriented lens. It asks how repeated AI-mediated interaction affects the human user, professional role, learning

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process, communication practice, and responsibility structure after a system has been introduced. This does not imply that human-centered AI ignores these issues; rather, it identifies a narrower analytic focus for the present framework: human outcomes in AI-mediated practice.

Human agency, trust, overreliance, and automation bias

The proposed AI Humanics framework places close attention on human agency. In AI-mediated environments, people can retain, lose, delegate, or reconfigure their sense of control. Research on algorithm aversion shows that users can reject algorithmic advice after observing errors, even when algorithms outperform human judgment [31]. Conversely, research on algorithm appreciation suggests that people can prefer algorithmic judgment under certain conditions [32]. Together, these findings indicate that human-AI trust is not a simple linear function of accuracy. It depends on perceived competence, transparency, prior experience, task type, context, and user expectations.

Recent reviews on appropriate trust in human-AI interaction emphasize the need to calibrate trust rather than simply increase it [4]. Overtrust can produce automation bias, in which users accept AI outputs despite contradictory evidence or contextual warning signs. Undertrust can prevent beneficial use of AI support. In healthcare, automation bias is especially important because AI recommendations can influence diagnosis, triage, treatment planning, documentation, and patient communication [5].

The sense of agency is also relevant. When AI participates in decisions, authorship and control can become ambiguous. Users can experience themselves as directing the tool, collaborating with it, or being led by it [6]. Integrative perspectives on algorithm aversion and appreciation further suggest that users' responses to AI depend on task uncertainty, perceived error costs, user expertise, and opportunities for human adjustment [33]. Generative AI adds a further concern because it can produce fluent, confident, and context-sensitive outputs that invite reliance even when the content is inaccurate, incomplete, or poorly grounded. Human-generative AI collaboration can improve immediate task performance while also affecting motivation and subsequent independent engagement [7].

AI literacy, learning, and educational transformation

AI literacy is another foundational domain. Long and Magerko [8] defined AI literacy as a set of competencies that enable individuals to critically evaluate, communicate, and collaborate with AI systems. Subsequent reviews have expanded this field by examining conceptual definitions, constructs, implementation strategies, and assessment instruments [9].

AI literacy is important because AI-mediated environments require more than technical familiarity. Users must understand what AI systems can and cannot do, recognize uncertainty, identify bias or hallucination, evaluate outputs against domain knowledge, and decide when human verification is necessary. In the context of generative AI, literacy also includes prompt formulation, source evaluation, critical interpretation, ethical awareness, and awareness of authorship and accountability.

Generative AI in higher education illustrates the need to evaluate learning outcomes beyond productivity. Systematic reviews and case-study syntheses suggest that generative AI can support feedback, tutoring, writing, programming, assessment design, and personalized learning [10,34]. However, these potential benefits are accompanied by concerns regarding academic integrity, superficial learning, inaccurate outputs, inequity of access, and dependency. A central AI Humanics question is therefore whether AI-supported learning transfers into durable human competence. For example, an AI writing assistant can improve the quality of a submitted essay, but a human-outcome evaluation asks whether the learner can later explain the argument, identify errors, and complete a similar task without AI support.

Ethics, governance, accountability, and research integrity

AI ethics and governance provide essential foundations. Reviews of AI ethics guidelines have identified recurrent principles such as transparency, justice, fairness, non-maleficence, responsibility, privacy, beneficence, and human oversight [11]. The European Commission's Ethics Guidelines for Trustworthy AI similarly emphasize human agency and

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oversight, technical robustness and safety, privacy and data governance, transparency, diversity and fairness, societal and environmental well-being, and accountability [35]. UNESCO's Recommendation on the Ethics of Artificial Intelligence further situates AI within human rights, dignity, inclusion, sustainability, and global governance [36].

Governance research has moved from principles toward implementation. Systematic reviews of AI governance highlight the need for institutional structures, regulatory frameworks, accountability mechanisms, risk management, and organizational responsibility [12]. Algorithmic auditing frameworks, model cards, and datasheets for datasets provide practical mechanisms for documenting systems, datasets, intended uses, limitations, and potential harms [13,37,38].

Generative AI can also create new research integrity risks. Guidelines on responsible use of generative AI in research and recent discussions of scholarly publishing emphasize authorship, citation accuracy, hallucinated references, undisclosed AI use, evidence distortion, and human verification [14,39]. Empirical work on hallucination, reference accuracy, generalization bias, and literature-synthesis reliability has shown that AI-generated references, summaries, and syntheses can be inaccurate or misleading [40-42]. These risks are relevant to AI Humanics because they reveal how AI can reshape not only outputs, but also the epistemic practices of researchers, students, clinicians, and professionals.

The governance literature also points to a need for organizational learning from AI failures. Incident databases and post-incident analysis are designed to create a collective memory of AI harms, near harms, and implementation failures so that organizations and sectors do not repeat avoidable errors [22]. Sector-led governance models and the AI Regulatory Readiness Index (ARRI) further show that accountability is shaped by institutional coordination, legal preparedness, and sector-specific obligations [23,43]. Formal legal frameworks such as the European Union AI Act add another layer by defining roles, obligations, and risk categories that affect developers, deployers, institutions, and affected communities [24]. For AI Humanics, these literatures clarify that responsibility and accountability should be studied not only as ethical ideals, but also as observable practices such as documentation, verification, incident reporting, escalation, role assignment, and regulatory alignment.

AI sociology and sociotechnical systems

AI Humanics also draws on sociological and sociotechnical perspectives. AI systems are not isolated tools; they are embedded in organizations, infrastructures, labor markets, professional hierarchies, regulatory regimes, and cultural expectations. Sociology of AI highlights how AI can reproduce or transform inequalities, redistribute power, restructure work, and shape data justice [15]. Critical AI scholarship further emphasizes that large-scale AI systems reflect the social, economic, linguistic, environmental, and political conditions under which they are produced [17,44].

A sociotechnical systems perspective argues that AI cannot be understood solely by examining algorithms or user interfaces. Instead, AI should be analyzed as part of a system of people, institutions, data practices, professional norms, economic incentives, and governance structures [16]. This perspective is particularly important for implementation because the same AI tool can have different effects depending on organizational culture, workflow, trust, expertise, training, and accountability.

For AI Humanics, AI sociology and sociotechnical systems research provide a bridge from individual human outcomes to institutional implementation. Human agency, expertise, care, and learning are not purely individual attributes; they are shaped by institutions, labor roles, incentives, documentation systems, professional standards, and access to resources. An AI system that supports one group can burden another. A tool that improves efficiency can redistribute responsibility or reduce opportunities for learning. AI Humanics therefore requires a multilevel perspective linking individual cognition and professional practice to organizational and societal change. This review does not comprehensively cover labor studies, industrial AI, public administration, or every sector-specific governance literature; rather, it incorporates selected sociotechnical and regulatory sources to clarify why future domain-specific extensions are needed.

Professional practice, healthcare, care, and expertise

Healthcare and professional education provide high-stakes examples of AI-mediated human outcomes. Systematic and scoping reviews on generative AI and LLMs in health professional and medical education suggest that these tools can support tutoring, assessment, clinical reasoning practice, feedback, simulation, and knowledge access [18,45]. At the

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same time, these reviews raise concerns about accuracy, bias, hallucination, overreliance, professionalism, confidentiality, and the preservation of clinical reasoning.

The possibility of AI-induced deskilling is particularly relevant. Reviews of AI in medicine have raised concerns that automation can reduce opportunities for professionals to practice core skills, weaken diagnostic vigilance, or shift expertise from internal reasoning to external tool management [19]. This does not imply that AI necessarily deskills professionals. AI can also augment expertise by expanding access to evidence, enabling simulation, supporting reflection, and reducing cognitive burden. The key issue is whether implementation preserves meaningful human participation in reasoning, communication, and responsibility.

Implementation science perspectives are therefore essential. Generative AI in healthcare requires translational pathways that address application, integration, governance, safety, workflow, professional acceptance, and evaluation [20,46]. Reviews of clinician acceptance and implementation barriers show that adoption depends on trust, usability, perceived usefulness, training, organizational readiness, legal concerns, and alignment with clinical workflow [25,26]. AI education programs for healthcare professionals further indicate that professional AI literacy must be deliberately developed rather than assumed [21].

Care is a central but often underdeveloped dimension. AI can support communication, documentation, patient education, and decision support, but care is not reducible to information transfer. Care involves attention, empathy, contextual understanding, responsibility, relational trust, and ethical responsiveness. AI Humanics therefore treats care and communication as a distinct domain: the question is not only whether AI improves efficiency or accuracy, but also whether it supports or risks eroding humane, accountable, and context-sensitive interaction.

Cross-domain critical analysis and rationale for AI

Across these domains, the reviewed literature provides substantial but uneven coverage of human outcomes in AI-mediated practice. Human-centered AI and human-AI interaction research offer mature design principles and interaction guidance, but they often begin from the system and examine how humans can use, supervise, or collaborate with it [1-3]. Trust, agency, overreliance, and automation bias research provides a direct account of judgment under AI influence, but it is often studied at the level of individual decisions or experimental tasks rather than accumulated professional practice [4-7]. AI literacy research identifies competencies for responsible AI use, but literacy is often operationalized as an individual educational outcome rather than as an institutional capacity that depends on time, evidence access, authority, workflow, and accountability [8-10].

AI ethics and governance scholarship provides essential principles and tools, including transparency, fairness, oversight, auditing, model reporting, documentation, and research-integrity guidance [11,13,14,37]. However, principles and documentation tools do not automatically produce responsible practice. Their effectiveness depends on whether human users and organizations can understand, enact, audit, and sustain them in real settings. Sociological and sociotechnical studies correct the tendency to view AI as an isolated tool by emphasizing institutions, power, labor, inequality, coloniality, and data justice [15-17]. However, macro-level sociotechnical analysis can be difficult to translate into measurable human-outcome indicators such as learning transfer, verification behavior, care communication, or expertise preservation.

Professional education and healthcare implementation research demonstrates why integration is needed in high-stakes domains [18-21]. Generative AI and LLMs can support tutoring, simulation, feedback, communication, evidence access, and implementation planning. The same tools can also contribute to overreliance, hallucination, deskilling, confidentiality risks, workflow disruption, and ambiguous responsibility. Incident-learning and regulatory literatures add another layer by showing that AI failures, legal obligations, and sector-specific governance arrangements shape how organizations adapt to AI-mediated environments [22-24].

Taken together, these literatures justify AI Humanics as a middle-level integrative framework rather than as a wholly new discipline. Its contribution is theoretical organization and operational translation. It gathers already established concerns into a set of human-outcome domains that can be examined across education, healthcare, research, governance, and

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other professional contexts. The framework is most useful where technical capability, human judgment, professional responsibility, and institutional implementation intersect.

Definition of AI Humanics

Based on the preceding synthesis, AI Humanics can be defined as follows: AI Humanics is a proposed integrative framework for examining how AI affects human agency, expertise, care, learning, trust, responsibility, and social implementation across AI-mediated practices.

This definition positions AI Humanics as complementary to AI engineering rather than separate from it. Many engineering, human factors, and human-centered design approaches already include usability, oversight, accountability, and human factors considerations [1,2,13]. AI Humanics does not deny this. Its narrower emphasis is to organize and evaluate human outcomes that emerge after AI systems are repeatedly used in education, care, research, governance, and professional work. The object of study is therefore not the AI system alone, but AI-mediated human practice at a specified analytic level.

To avoid ambiguity, the term AI-mediated human practice should be operationalized at one or more levels. At the individual or professional level, it refers to the learner, clinician, researcher, worker, or citizen whose agency, learning, expertise, trust, or responsibility is affected by AI use. At the interactional or team level, it refers to communication, care, verification, collaboration, and role negotiation among humans and AI systems. At the institutional or sectoral level, it refers to workflow, governance, accountability, incident learning, regulation, and implementation fit. Future empirical studies should specify which level is being evaluated.

Seven-domain AI Humanics framework

The proposed framework consists of seven interrelated domains. These domains are analytically distinct but practically interdependent. Human agency refers to the extent to which people remain active, reflective, and responsible participants in AI-mediated tasks [4,6,33]. Expertise transformation refers to how AI changes professional knowledge, skill, judgment, and identity [18,19,21]. Care and communication refer to the effects of AI on relational, explanatory, educational, and supportive interactions [18,20,25]. Learning transfer refers to whether AI-supported learning produces durable human competence beyond immediate AI-assisted task completion [8,10,34]. Trust calibration refers to the alignment between user trust and system reliability [4,5,33]. Responsibility and accountability refer to how responsibility is assigned, documented, verified, and enacted in AI-mediated practice [12,13,22,24]. Social implementation fit refers specifically to contextual alignment at workflow, organizational, regulatory, and sectoral levels [16,20,23,24,26]. It is not intended as a catch-all category for all social effects; individual agency, trust, learning, expertise, care, and responsibility are addressed by the other domains.

A system that improves efficiency can reduce learning opportunities [10,34]. A tool that increases trust can also increase overreliance [4,5]. A governance policy can assign accountability without ensuring that users have the literacy, time, authority, or documentation tools needed to act responsibly [12,13,24]. AI Humanics therefore emphasizes interactions among domains rather than treating them as independent checklist items. The proposed multi-level framework linking human outcomes to AI-mediated practice is illustrated in Figure 7.

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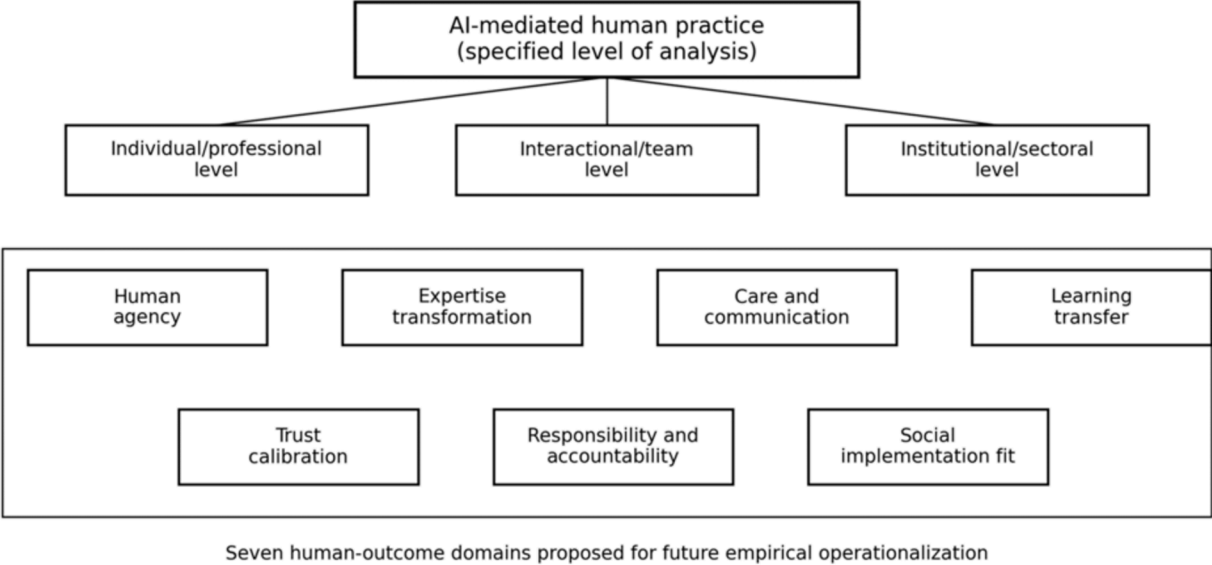


FIGURE 1: AI Humanics as a multi-level framework linking human outcomes to AI-mediated practice. Individual/professional, interactional/team, and institutional/sectoral levels are connected to the seven proposed domains.

Table 1 summarizes adjacent fields in a balanced way by distinguishing typical emphasis, contribution, and integration questions rather than claiming that the contributing fields lack human-oriented perspectives.

Field	Typical emphasis in reviewed literature	What AI Humanics draws from it	Integration question for AI Humanics
Human-centered AI	Human values, safe design, reliability, usability, human control	Design and governance principles for human-aligned AI	After a human-centered system is introduced, what human capacities and roles change over time?
Human-AI interaction	Interaction patterns, user experience, mental models, decision support	Task-level understanding of how users engage with AI outputs	How do repeated interactions affect agency, trust, expertise, and communication beyond a single task?
AI literacy	Competencies for understanding, evaluating, and using AI	Educational constructs and assessment approaches	How do AI competencies translate into durable learning, verification behavior, and responsible practice?
AI ethics and governance	Transparency, fairness, accountability, oversight, auditing, documentation	Normative principles and practical governance mechanisms	How are governance requirements enacted by human users, teams, and institutions?
AI sociology and sociotechnical systems	Institutions, labor, inequality, power, data justice, organizational context	Multilevel understanding of AI as embedded in social systems	How can macro-level sociotechnical concerns be connected to measurable human and professional outcomes?
Implementation science	Adoption, workflow, barriers, facilitators, sustainability	Methods for studying real-world adoption and organizational fit	How does implementation change human skills, responsibilities, relationships, and accountability?
AI incident and regulatory studies	Incident reporting, organizational learning, sectoral governance, legal obligations	Evidence that failures and regulation shape institutional adaptation	How do incident learning and legal preparedness influence human responsibility and implementation fit?
AI Humanics	Human outcomes in AI-mediated practice	Integrates agency, expertise, care, learning, trust, responsibility, and implementation	What human capacities and practices should be measured alongside system performance?

TABLE 1: Adjacent fields and the proposed contribution of AI Humanics.

Table 2 operationalizes the seven proposed domains using narrower research questions and example indicators that can guide future empirical studies.

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Domain	Operational focus	Example indicators	More specific research questions
Human agency	Active human participation in AI-mediated tasks	Documented human rationale; override or contestation rate; time spent reviewing AI output; sense-of-agency scale	Does AI support change the proportion of decisions accompanied by independent human rationale and justified override behavior?
Expertise transformation	Changes in professional skill, judgment, and identity	AI-free performance after AI use; error-detection accuracy; skill-practice frequency; perceived role change	After repeated AI support, which domain skills improve, remain stable, or decline on AI-free transfer tasks?
Care and communication	Relational and explanatory quality of AI-mediated communication	Patient or learner ratings; expert review of AI-drafted messages; empathy and clarity scores; documentation burden	Does AI-assisted communication improve clarity without reducing contextual responsiveness or accountable human engagement?
Learning transfer	Durable competence beyond AI-assisted task completion	Delayed AI-free assessment; transfer task performance; reflective explanation quality; independent problem solving	Do learners who use AI support perform better on delayed, AI-free tasks than learners who only complete AI-assisted tasks?
Trust calibration	Alignment between trust and actual system reliability	Overreliance error rate; agreement with correct versus incorrect AI suggestions; uncertainty recognition; calibration curves	Do users accept reliable AI outputs while rejecting misleading outputs at rates appropriate to system performance?
Responsibility and accountability	Assignment, documentation, verification, and enactment of responsibility	AI-use disclosure; verification logs; named accountable role; audit trail; escalation and incident-reporting pathway	Does an implementation specify who verifies AI outputs, how verification is documented, and how errors are escalated?
Social implementation fit	Workflow, organizational, regulatory, and sectoral alignment	Workflow burden; training completion; policy alignment; regulatory role mapping; incident-learning process; equity monitoring	Does the AI implementation fit local workflow and legal obligations without creating hidden burdens or inequitable effects?

TABLE 2: Proposed AI Humanics evaluation domains.

Illustrative retrospective applications

The seven domains can be applied retrospectively to common AI-use scenarios. These examples are illustrative and are not empirical validation of the framework.

In AI-supported education, a generative AI tutor or writing assistant can be evaluated not only by immediate performance or user satisfaction, but also by learning transfer, trust calibration, and agency. Relevant measures include delayed AI-free writing or problem-solving tasks, learner explanations of why an AI suggestion was accepted or rejected, and error-detection performance when the AI output contains plausible but incorrect information [8,10,34].

In healthcare or health professional education, an LLM-based simulation, documentation assistant, or clinical communication tool can be evaluated across expertise transformation, care and communication, trust calibration, and responsibility. Relevant measures include performance on clinical reasoning tasks without AI support, expert ratings of patient-centered communication, documentation of human verification, and the presence of escalation procedures for uncertain or potentially unsafe AI outputs [18,20,46].

In AI-assisted research, literature summarization or citation generation tools can be evaluated through responsibility and accountability, trust calibration, and social implementation fit. Relevant measures include citation accuracy, source-verification logs, disclosure of AI use, audit trails, and institutional policies for correcting AI-generated errors [14,22,40].

In public-sector or regulated infrastructure contexts, social implementation fit can be evaluated by mapping AI responsibilities to organizational roles, incident-reporting pathways, sector-specific standards, and legal obligations. Sector-led governance and the ARRI show that the same AI capability can face different accountability structures depending on sector and jurisdiction [23,24,43].

Discussion

This narrative review and conceptual synthesis propose AI Humanics as an integrative framework for studying human outcomes associated with AI use. Its purpose is not to introduce a replacement label for human-centered AI, AI ethics, AI literacy, AI sociology, sociotechnical systems research, or implementation science. Rather, AI Humanics is presented as a middle-level framework that connects these adjacent fields around a specific object of study: AI-mediated human practice.

The intended contribution of AI Humanics is a shift from an AI-centered unit of analysis to a human-outcome unit of analysis. Much AI research begins with the system: its accuracy, robustness, usability, fairness, explainability, or efficiency [1,2,11,13]. These dimensions are essential, but they do not fully capture downstream consequences of AI-mediated practice. AI Humanics begins from a complementary question: when AI becomes part of work, education, care, research, governance, and social life, how are human capacities and practices affected?

This distinction has practical implications. An AI tutor can improve immediate task completion, but an AI Humanics perspective asks whether learners acquire durable competence, reflective judgment, and transferable understanding [8,10,34]. An AI clinical assistant can produce fluent explanations, but an AI Humanics perspective asks whether clinicians preserve patient-centered communication, contextual reasoning, and accountability [18-20]. An AI research assistant can summarize papers efficiently, but an AI Humanics perspective asks whether researchers maintain evidence verification, citation integrity, and epistemic responsibility [14,40,42]. In each case, system performance is necessary but insufficient for evaluating human outcomes.

AI Humanics builds on human-centered AI but extends it toward human-outcome analysis. Human-centered AI asks whether systems are designed with human needs, values, usability, and safety in mind [1,2,30]. AI Humanics asks what happens to humans and institutions after these systems are introduced and repeatedly used. A tool can be human centered in design but still produce problematic outcomes if it encourages overreliance, weakens skill development, narrows professional judgment, or redistributes responsibility in opaque ways [4,5,10,13,19]. This distinction is intended to complement, not criticize, human-centered design.

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Accountability is one domain where operationalization is especially important. Within AI Humanics, accountability can be assessed through observable mechanisms rather than treated only as a principle. These mechanisms include whether AI use is disclosed, whether human verification is required and documented, whether an accountable role is named, whether audit trails are retained, whether error escalation pathways exist, whether incidents or near misses are reported, and whether the implementation is aligned with applicable legal or sectoral obligations [13,14,22,24]. These indicators can be adapted to education, healthcare, research, public administration, or other domains.

Expertise transformation is another important domain. AI does not simply replace or augment expertise in a uniform way. It can automate routine components of work, expand access to knowledge, support simulation, reduce cognitive burden, or enable new forms of reflection [18,20,21]. At the same time, it can reduce opportunities to practice foundational skills, obscure the reasoning process, or make professionals dependent on outputs they cannot independently evaluate [19]. The key research question is not whether AI destroys or enhances expertise in general, but which skills are displaced, preserved, newly required, or redistributed under specific implementation conditions.

Care and communication are included as core domains because many professional practices cannot be reduced to correctness or efficiency [18,20,25]. In healthcare, education, counseling, leadership, and community engagement, communication is not merely a channel for information transfer. It is part of the relational and ethical substance of practice. AI can support communication by improving clarity or reducing documentation burden, but it can also standardize expression or create a false sense of personalization. AI Humanics therefore asks whether AI-mediated communication supports understanding, trust, and accountable human interaction rather than evaluating communication solely through fluency or satisfaction.

The domain of social implementation fit emphasizes that AI-mediated human outcomes occur within institutions [16,20,23,24,26]. This domain is limited to contextual alignment at workflow, organizational, regulatory, and sectoral levels. It does not replace the other six domains. Rather, it asks whether the conditions needed to support those domains are present: training, workflow compatibility, authority to verify or override AI outputs, documentation practices, incident-learning systems, regulatory role mapping, and equity monitoring.

Future research should measure human outcomes alongside system outcomes. Depending on the setting, these outcomes can include agency, trust calibration, learning transfer, expertise preservation, communication quality, responsibility awareness, verification behavior, incident reporting, regulatory alignment, and perceived role change. Research designs should move beyond short-term task performance where appropriate. Longitudinal studies, transfer tasks, pre-post designs, qualitative interviews, ethnography, mixed-methods evaluations, and implementation studies can help capture gradual transformations in skill, judgment, professional identity, and institutional accountability.

This review has limitations. First, it is a narrative review and conceptual synthesis rather than a systematic review or meta-analysis. Although the revised manuscript reports a candidate matrix, screening stages, and final reference set, the search remained purposive and iterative rather than fully reproducible. Second, the seven domains were developed through manual conceptual mapping rather than formal thematic synthesis, expert consensus, or empirical validation. They should therefore be treated as provisional. Third, the evidence base is weighted toward healthcare, education, human-AI interaction, AI ethics, and implementation science. Public administration, law, labor studies, industrial AI, and sector-specific governance are discussed only selectively. Fourth, the framework has not been tested against prospective empirical data. Its practical value remains unproven until the domains are operationalized and evaluated in real settings. Empirical validation across multiple application domains will be necessary to establish the generalizability of the proposed framework. Finally, the term AI Humanics may overlap with other uses of humanics; future work should clarify its boundaries and avoid treating it as a fully established discipline before sufficient empirical and conceptual work has accumulated.

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Conclusions

Generative AI influences not only the capabilities of machines, but also the conditions under which humans learn, decide, communicate, care, verify, and take responsibility. Existing fields such as human-centered AI, human-AI interaction, AI ethics, AI literacy, AI sociology, sociotechnical systems research, responsible AI, and implementation science provide essential perspectives on this transformation. This narrative review and conceptual synthesis propose AI Humanics as an integrative framework for studying human outcomes in AI-mediated practice. AI Humanics is defined as a proposed framework for examining how AI affects human agency, expertise, care, learning, trust, responsibility, and social implementation. Its intended contribution is not to replace existing human-focused AI approaches, but to organize their insights into a set of domains that can be evaluated alongside AI capability. This perspective is particularly relevant in the generative AI era, where AI systems increasingly participate in writing, explanation, education, evidence synthesis, clinical communication, decision support, governance, and professional knowledge work.

The proposed seven-domain framework offers a provisional foundation for future research and practice. Human agency, expertise transformation, care and communication, learning transfer, trust calibration, responsibility and accountability, and social implementation fit can serve as conceptual domains for empirical studies, educational design, governance frameworks, and implementation evaluations. Future work should operationalize these domains, develop measurement tools, test the framework across domains, and examine how regulatory and institutional settings shape human outcomes. AI Humanics should therefore be understood as a hypothesis-generating and framework-building contribution rather than as a validated discipline. By making AI-mediated human practice an explicit object of study, the framework can help researchers and practitioners ask a more complete question: not only what AI can produce, predict, or automate, but what kinds of human judgment, expertise, care, learning, responsibility, and institutional practice are shaped through AI use.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Disclosures

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

AI Disclosure Statement

The authors used ChatGPT 5.5 (OpenAI, San Francisco, CA, USA) during manuscript preparation for language editing. The tool was also used to assist with the refinement of academic wording and the preparation of disclosure and availability statements. All AI-assisted outputs were manually reviewed, edited, and verified by the authors. All AI-assisted outputs

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were reviewed and verified by the authors, who take full responsibility for the accuracy, integrity, and originality of the content.

Data Availability Statements

Data sharing is not applicable. This work is theoretical; no datasets were generated or analyzed.

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How to cite this article:

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How to cite this article:

Harada Y (July 27, 2026) Artificial Intelligence Humanics as an Integrative Framework for Human Outcomes in the Generative Artificial Intelligence Era: A Narrative Review and Conceptual Synthesis. Cureus J AI Augment Res 1 : es44568-026-00185-3. DOI <https://doi.org/10.7759/s44568-026-00185-3>

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