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How ProSocial AI Can Catalyze Quality of Life and Positive Social Change at Scale: Double Literacy and the ProSocial AI Index

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Article

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Abstract

Artificial intelligence increasingly mediates how people learn, work, seek care, form relationships, access public services, and respond to environmental risk. Its quality-of-life effects extend beyond technical performance and economic productivity. This conceptual article develops the ProSocial AI-Quality of Life Catalyst Model (PAI-QOL), a multilevel framework explaining when and how AI can contribute to futures that are pro-people, pro-planet, and pro-potential. ProSocial AI is defined as AI deliberately designed, deployed, and governed to generate demonstrable and fairly distributed gains in multidimensional quality of life, strengthen human and collective capabilities, and protect the ecological conditions of future well-being. A problem-driven integrative synthesis identifies four conversion pathways: agency and capability, relational and social-capital, institutional and public-value, and regenerative and intergenerational. Their benefits depend on four enabling conditions: Double Literacy, meaningful participation, contestability, and proportionality. The model connects the 4T architecture of tailored, trained, tested, and targeted AI with a 4 x 4 lens spanning aspirations, emotions, thoughts, and sensations across individual, community and institutional, national and systemic, and planetary and intergenerational levels. Four propositions translate the framework into testable claims. A multidimensional measurement strategy distinguishes genuine prosocial contribution from intention, compliance, or branding. ProSocial AI emerges as a disciplined direction for innovation that expands agency, reinforces trustworthy relationships and institutions, preserves future capability, and produces social value within planetary limits.

1. Introduction

Artificial intelligence is moving from a collection of specialized applications toward a pervasive layer of social infrastructure. It helps determine which information people encounter, how work is organized, which risks institutions detect, how services are allocated, and which options appear plausible. Generative systems add a further dimension. They participate in language, interpretation, advice, creativity, and social exchange: activities through which people understand themselves and the world. AI consequently enters quality of life through many doors at once.

The same system can reduce administrative burden and intensify monitoring. A conversational tool can make health information intelligible, reinforce a mistaken interpretation, or cultivate dependence. A recommendation system can connect people with useful communities while narrowing exposure and rewarding outrage. A climate model can improve early warning and consume substantial energy, water, and material resources. AI's contribution to quality of life rests on the interaction among technical properties, human capacities, institutional incentives, social relationships, political power, and ecological conditions.

Recent evidence confirms the need for this wider frame. In *Applied Research in Quality of Life*, Höfer (2026) locates AI within a bio-psycho-social account of work, mental health, social connection, and human flourishing. Teng and Cho (2026) document psychological harms associated with AI-driven social media curation. Shi and Sirgy (2026), using a panel of 138 countries, find that the relationship between

national AI development and quality of life changes with governance quality: weak governance is associated with a more negative relationship, while stronger governance creates more favorable conditions. Together, these studies move the debate beyond technological optimism. They also leave an important theoretical question open. Through which mechanisms does AI become quality of life, social capital, or capability, and under which conditions does that conversion reverse?

This article addresses that question through the ProSocial AI-Quality of Life Catalyst Model (PAI-QOL). It treats AI as a potential catalyst rather than an autonomous cause. A catalyst changes the conditions and pace of a process. Its effects depend on the materials, environment, and reactions around it. AI can therefore accelerate learning, access, coordination, care, and ecological intelligence. It can also accelerate extraction, polarization, dependency, surveillance, and environmental strain. The relevant question concerns direction: which human and planetary processes are being accelerated, for whose benefit, under whose control, and with which consequences over time?

The article develops ProSocial AI as a quality-of-life orientation with three linked commitments. A **pro-people** orientation advances present well-being, dignity, agency, inclusion, relational quality, and fair access to the conditions of a good life. A **pro-planet** orientation protects and, where feasible, regenerates the ecological systems that sustain human and non-human life. A **pro-potential** orientation preserves and expands people's capabilities, communities' problem-solving capacity, institutional learning, and the option space available to future generations. These orientations are mutually dependent. Present well-being that erodes future capacity is fragile. Environmental protection that disregards justice loses legitimacy. Capability expansion without social trust can deepen unequal power.

The article advances the premise that AI can strengthen social capital and shared quality of life when it is tailored, trained, tested, and targeted around legitimate human and planetary needs. It develops that premise in four ways. First, it offers a definition that can support evaluation and guard against “prosocial washing.” Second, it specifies four causal pathways between AI and quality of life. Third, it identifies four boundary conditions that determine whether these pathways yield beneficial, neutral, or harmful outcomes. Fourth, it converts the framework into four propositions and a measurement strategy suitable for empirical research.

The contribution is timely. Quality-of-life scholarship provides the multidimensional concepts needed to evaluate AI's consequences. AI research provides rapidly developing evidence about performance, interaction, work, and risk. Social capital theory clarifies how trust, reciprocity, networks, and collective efficacy influence well-being. The capability approach distinguishes delivered outputs from people's real freedom to pursue valued lives. Planetary health links human flourishing to ecological viability. Their integration creates a richer account of technological progress: one grounded in experienced life, relational and institutional conditions, future capability, and the biosphere on which every digital system ultimately depends.

2. Conceptual and Methodological Approach

2.1 Quality of life as the evaluative horizon

Quality of life is well suited to the assessment of AI because it resists reduction to a single outcome. The WHOQOL tradition defines quality of life in relation to people's perceptions of their position in life, their cultural and value contexts, and their goals, expectations, and concerns (WHOQOL Group, 1995, 1998). Subjective well-being research distinguishes life evaluation, positive and negative affect, and eudaimonic dimensions such as meaning and functioning (Diener, 1984; Diener et al., 2018). The capability approach asks whether people possess substantive freedoms to be and do what they have reason to value (Sen, 1999; Nussbaum, 2011). The OECD well-being framework adds current outcomes, inequalities, and the resources needed for future well-being (OECD, 2024).

These traditions reveal why an AI system's accuracy or efficiency cannot stand as a proxy for quality-of-life contribution. A benefits chatbot may process claims quickly while confusing applicants and weakening trust. An educational assistant may raise short-term task completion while diminishing curiosity or independent reasoning. A productivity system may increase output while intensifying work, reducing autonomy, and transferring risk to employees. Technical performance remains necessary in many applications. Quality-of-life value emerges through the lived and distributed consequences of that performance.

A quality-of-life horizon also expands time. AI can create immediate convenience alongside delayed skill erosion. It can provide short episodes of emotional relief while altering social habits. It can improve resource efficiency and generate rebound effects as usage scales. Evaluation therefore requires attention to current experience, cumulative adaptation, institutional development, and intergenerational consequences.

2.2 A problem-driven integrative synthesis

The PAI-QOL model was developed through a problem-driven integrative conceptual synthesis. This approach is appropriate where a fast-moving phenomenon cuts across literatures that use different constructs and levels of analysis. The purpose is theory construction rather than a systematic estimate of effect size.

The synthesis followed four stages. **Construct clarification** identified the minimum properties required for ProSocial AI to carry analytical meaning. **Mechanism extraction** examined how established theories describe the conversion of resources and environments into well-being, agency, relationships, trust, and future capability. **Multilevel integration** connected individual experience with community, organizational, national, and planetary conditions. **Proposition and indicator development** translated the resulting architecture into claims and observable implications.

The synthesis draws on quality-of-life studies, subjective well-being, the capability approach, self-determination theory, social capital, public value, institutional governance, human-computer interaction, responsible AI, environmental sustainability, and planetary health. It also incorporates emerging

empirical work on AI companionship, algorithmic curation, human-AI agency, deskilling, and AI infrastructure. Recent studies show both supportive and adverse patterns. AI companions can reduce momentary loneliness in controlled and short-term settings (De Freitas et al., 2025), while observational evidence indicates that outcomes vary with loneliness and existing social connectedness (Nakagomi et al., 2026). Algorithmic curation can also deepen digital isolation and psychological harm (Teng & Cho, 2026). AI can support exploration and innovation while redistributing agency within organizations (Krakowski, 2025). It can create capacity-hostile environments when repeated offloading weakens the cultivation of valuable human skills (Ferdman, 2026). Such findings reinforce a conditional model.

Generative AI was used under the author's direction to support drafting and language development. The author selected the conceptual structure and sources, reviewed and revised the manuscript, and assumes responsibility for the final argument, accuracy, and citations.

3. Defining ProSocial AI

3.1 From ethical intention to demonstrated contribution

The language surrounding beneficial AI is already crowded. "Ethical," "responsible," "trustworthy," "human-centered," and "human-compatible" AI each offer useful principles. Many frameworks emphasize safety, fairness, privacy, transparency, reliability, human rights, oversight, and human-centered interaction (Amershi et al., 2019; European Union, 2024; Floridi & Cowls, 2019; Jobin et al., 2019; OECD, 2019; Shneiderman, 2022; UNESCO, 2021; National Institute of Standards and Technology, 2023). ProSocial AI shares these foundations and adds an outcome orientation centered on multidimensional quality of life and social capability.

ProSocial AI is defined here as AI deliberately designed, deployed, and governed to generate demonstrable and fairly distributed improvements in multidimensional quality of life, strengthen human and collective capabilities, and protect the ecological conditions of future well-being. Its legitimacy depends on participation, contestability, proportionality, and continued evidence of net contribution.

Several implications follow.

First, prosociality concerns effects as well as intention. A developer's public-interest purpose does not establish a prosocial outcome. Evidence must show how benefits and harms are distributed, whether people retain meaningful choice, and whether the system remains responsive to correction.

Second, prosociality is relational. An AI system changes interactions among users, professionals, organizations, communities, vendors, and public authorities. A system that helps one actor by shifting hidden burdens to another requires wider appraisal.

Third, prosociality is dynamic. Model behavior, user practices, institutional incentives, and population effects change. A system can begin as a useful supplement and evolve into an infrastructure that is difficult to question or exit. Monitoring and adaptation belong inside the definition.

Fourth, prosociality is bounded by ecology. Digital services depend on physical infrastructures, electricity, water, minerals, land, logistics, and labor. AI's ecological burden forms part of its quality-of-life account. The environmental impact of AI servers is already material and highly sensitive to deployment scale, grid composition, water conditions, infrastructure efficiency, and location (Xiao et al., 2025).

3.2 Pro-people, pro-planet, pro-potential

The three orientations convert the definition into a substantive direction.

Pro-people places multidimensional human well-being at the center of design and governance. It includes health, safety, material security, autonomy, competence, belonging, dignity, cultural recognition, and the capacity to influence decisions. It also includes distribution. Average gains can coexist with severe harm among groups that have less access, representation, or recourse. A pro-people assessment therefore asks who benefits, who bears risk, whose knowledge shaped the system, and who can challenge its operation.

Pro-planet locates quality of life within ecological systems. AI may support climate modeling, pollution detection, energy coordination, conservation, resilient agriculture, and disaster preparedness. Each use also carries an infrastructure footprint, political economy, and opportunity cost (Crawford, 2021). Pro-planet AI requires lifecycle visibility, resource proportionality, low-impact design, responsible siting, and a credible relationship between ecological burden and social value. It further recognizes environmental justice: water, energy, land, emissions, and e-waste burdens often fall on communities far from the users receiving benefits.

Pro-potential focuses on what people, institutions, and future generations remain able to become. It values learning, judgment, creativity, curiosity, civic competence, occupational mastery, and collective problem-solving. AI can enlarge potential by lowering barriers to knowledge, translation, analysis, and creation. It can narrow potential through habituated dependence, standardized expression, constrained option sets, and declining opportunity to practice difficult skills. Pro-potential design seeks augmentation that leaves people more capable after use.

The three orientations provide a demanding standard. A technically safe system may still fail to create meaningful human value. A socially useful application may carry an avoidable ecological burden. An efficient service may weaken the capacities needed to supervise it. ProSocial AI treats these tensions as design and governance work rather than externalities.

3.3 The 4T architecture

The 4T architecture locates prosocial intent across the AI lifecycle and extends earlier ProSocial AI work (Walther, 2024, 2026a, 2026b).

1. **Tailored**: The system is fitted to a legitimate need, context, population, language, and level of risk. Tailoring includes accessibility, cultural relevance, and recognition of limits. It avoids the assumption that a general-purpose model is equally appropriate for every person or institution.

2. **Trained**: Data, objectives, feedback, and development practices reflect the intended social purpose. Training choices address representation, provenance, labor conditions, privacy, and the values embedded in optimization targets.

3. **Tested**: Evaluation extends beyond benchmark performance. It examines safety, subgroup performance, usability, autonomy, trust, relational effects, capability retention, institutional consequences, and environmental load under realistic conditions.

4. **Targeted**: Deployment is bounded to settings where expected quality-of-life contribution justifies risk and resource use. Targeting establishes responsibility, human decision rights, escalation, recourse, review intervals, and exit conditions.

The 4Ts create lifecycle discipline. They also expose a recurring failure pattern: systems are often broadly trained, lightly adapted, tested on technical metrics, and deployed wherever adoption appears commercially or administratively attractive. ProSocial AI reverses this sequence by beginning with a valued human or planetary outcome and tracing the conditions needed to support it.

4. The ProSocial AI-Quality of Life Catalyst Model

The PAI-QOL model explains how the 4T architecture may be converted into quality-of-life outcomes. It contains four pathways: agency and capability, relational and social capital, institutional and public value, and regenerative and intergenerational. The pathways interact. Clearer information can improve agency; greater agency can support participation; responsive participation can strengthen institutional trust; trusted institutions can coordinate ecological action; ecological security supports health, livelihood, and future opportunity. Figure 1 summarizes the model’s architecture and evaluative logic.

4.1 Agency and capability pathway

The first pathway concerns a person's capacity to understand, choose, learn, and act. AI can reduce cognitive and administrative friction by summarizing information, translating language, generating options, simulating consequences, and adapting support. These functions may increase perceived competence, access to knowledge, and the feasibility of action. They are especially valuable where time, disability, language, expertise, or geography creates barriers.

Self-determination theory offers a useful mechanism. Well-being tends to improve when environments support autonomy, competence, and relatedness (Ryan & Deci, 2017). AI may support autonomy by clarifying options, competence by providing feedback and scaffolding, and relatedness by improving communication. This augmentation potential coexists with the organizational tendency to convert

assistance into substitution when efficiency becomes the dominant objective (Raisch & Krakowski, 2021). The capability approach adds a crucial distinction: resources create value when people can convert them into real opportunities (Sen, 1999). A technically capable model therefore becomes a quality-of-life resource only when people can access, understand, trust, adapt, and contest its use.

Agency can also decay. The ease of generative output creates incentives to offload interpretation, writing, recall, planning, and judgment. Occasional assistance may support experimentation and learning. Repeated substitution can move from integration toward reliance and addiction, particularly when systems are frictionless, personalized, and embedded in essential workflows. Ferdman (2026) describes the broader structural risk: environments saturated with automation can become hostile to capacity cultivation because people lose occasions to practice, observe skilled others, and gain agential control.

ProSocial design therefore makes capability retention an outcome. Useful features include graduated assistance, visible uncertainty, explanations suited to the user's level, opportunities to compare human and system reasoning, deliberate practice modes, and clear escalation to human expertise. In high-stakes contexts, meaningful human oversight requires sufficient knowledge, time, authority, and access to evidence. A ceremonial approval click provides little agency.

Proposition 1

(agency and capability). AI use will improve quality of life when it expands informed choice, competence, and the real opportunity to act while preserving or strengthening the capabilities required for future independent judgment. Effects will weaken or reverse as cognitive offloading, opacity, and repeated substitution produce dependency or skill erosion.

4.2 Relational and social-capital pathway

Quality of life is deeply relational. People benefit from close ties, reciprocal support, recognition, belonging, and participation in networks that enable collective action. Social capital captures several of these resources, including trust, norms of reciprocity, networks, and the capacity to coordinate (Putnam, 2000; Woolcock & Narayan, 2000). Its forms matter. Bonding capital supports solidarity within groups. Bridging capital connects people across social difference. Linking capital enables relationships with institutions and actors holding authority or resources. Each can support well-being; bonding can also enable exclusion, conformity, or hostility toward outsiders (Portes, 1998).

AI can influence social capital by translating communication, matching people with support, coordinating volunteers, reducing professional paperwork, identifying unmet needs, and helping communities share knowledge. In education, it may free teacher time for feedback and care. In health, it may help patients prepare for consultations and understand follow-up instructions. In civic life, it may make public information accessible and support deliberation across languages.

The relational pathway also contains a substitution risk. Conversational systems can produce language that feels responsive, patient, and affirming. Short-term experiments suggest that AI companions can reduce momentary loneliness (De Freitas et al., 2025). Large observational studies indicate that benefits vary with loneliness and social connectedness (Nakagomi et al., 2026). These findings support careful differentiation between immediate emotional relief and longer-term changes in social behavior, network quality, and reliance. The World Happiness Report 2025 similarly underscores the importance of caring and sharing for well-being, directing attention toward the human relationships surrounding any digital intervention (Helliwell et al., 2025).

A prosocial relational system scaffolds human connection where possible. It helps users rehearse difficult conversations, find communities, reach professional support, or sustain relationships across barriers. It avoids commercial incentives that reward dependency, exclusive attachment, or prolonged engagement for its own sake. It communicates the artificial nature and limits of the interaction. In care-related settings, it supports continuity and escalation because relational trust depends on responsibility and follow-through as well as empathic language.

ProSocial AI also protects pluralism. Recommender systems can produce dense bonding within homogeneous networks while eroding bridging ties and shared reality. The OECD's recent evidence shows declining in-person contact and worsening social connection among some young people and men, with disconnection overlapping socioeconomic disadvantage (OECD, 2025). AI systems that mediate social discovery and information therefore carry a public responsibility to avoid deepening isolation, humiliation, or polarization.

Proposition 2

(relational and social capital). AI use will improve quality of life and social capital when it increases reciprocal human support, bridging and linking ties, inclusive participation, and time for accountable care. Effects will weaken or reverse when synthetic interaction displaces human relationships, recommender incentives reward division, or simulated empathy creates attachment without responsibility.

4.3 Institutional and public-value pathway

Institutions shape quality of life by organizing access to health, education, justice, welfare, work, finance, and public participation. AI can improve institutional responsiveness through translation, triage, case prioritization, pattern detection, service navigation, and administrative support. These gains matter most when they reduce burdens that fall disproportionately on people with limited time, mobility, money, literacy, or institutional familiarity.

Institutional efficiency alone offers an incomplete account. Public value includes effectiveness, fairness, legitimacy, rights, and public trust (Moore, 1995). A faster decision can lower quality of life if affected people cannot understand the basis, correct an error, or reach a responsible person. An accurate

prediction can create stigma when institutions treat probabilistic risk as destiny. Automated systems can also redistribute discretion from frontline professionals to vendors, data teams, or senior managers, often without public visibility.

The emerging empirical literature supports this institutional emphasis. Shi and Sirgy (2026) find that governance quality moderates the association between national AI development and quality of life. Their results suggest that technical capacity creates broad well-being gains only through institutional conditions that can direct and distribute it. This article extends that insight to the level of mechanism. Governance operates through procurement standards, documentation, impact assessment, professional capacity, participation, contestability, audit access, redress, and the authority to pause or terminate systems.

Trust is an outcome and a condition. Reliable services can strengthen trust when people feel respected and receive explanations and remedies. Opaque automation can reduce trust even when average performance improves. Linking social capital becomes particularly relevant: people need usable relationships with institutions and credible routes to influence decisions. A system that makes government more efficient and less answerable creates a brittle form of modernization.

ProSocial institutional design assigns responsibility before deployment. It identifies the decision owner, the role of AI, the evidence available to professionals and affected people, the process for appeal, and the thresholds for review. Procurement contracts require access to performance data, incident reporting, subgroup analysis, security evidence, environmental information, and termination rights. Internal and independent audit processes can connect these requirements across the system lifecycle (Raji et al., 2020). Institutions also need internal literacy; oversight cannot be outsourced entirely to vendors whose interests differ from the public mandate.

Proposition 3

(institutional and public value). AI deployment will improve quality of life and institutional trust when gains in access, responsiveness, and decision support are combined with transparency, professional capability, meaningful contestability, and enforceable responsibility. Effects will weaken or reverse as opacity, surveillance, accountability diffusion, and asymmetric power reduce dignity, fairness, or recourse.

4.4 Regenerative and intergenerational pathway

Quality of life depends on breathable air, safe water, stable climates, biodiversity, food systems, resilient infrastructure, and communities able to respond to shocks. Planetary health makes this dependence explicit by connecting human health and flourishing with the state of natural systems (Whitmee et al., 2015). AI can contribute through forecasting, environmental monitoring, grid management, materials discovery, disaster response, land-use analysis, and precision support for agriculture and conservation.

These applications can produce significant social value. Early warnings may save lives. Better heat mapping can guide urban investment toward vulnerable neighborhoods. Biodiversity monitoring can make ecological loss visible. Resource optimization can reduce waste. Their contribution, however, must be assessed alongside the material system required to build and operate AI. Server manufacturing, data centers, energy generation, cooling, water use, semiconductor supply chains, and hardware turnover create ecological and social burdens.

Recent modeling illustrates the scale and uncertainty. Xiao et al. (2025) estimate that AI-server deployment in the United States could generate annual water footprints of 731 to 1,125 million cubic meters and additional annual emissions of 24 to 44 million tonnes of carbon dioxide equivalent between 2024 and 2030, depending on expansion. Efficiency, location, grid decarbonization, and water conditions substantially change the result. Their analysis also identifies rebound effects: greater efficiency can lower the cost of use and stimulate enough additional demand to offset savings.

A pro-planet orientation therefore applies proportionality. High-resource AI may be justified when it delivers substantial and otherwise unavailable value in public health, climate resilience, science, accessibility, or essential services. The same footprint carries a weaker justification when used to optimize low-value persuasion, synthetic content volume, or addictive engagement. The assessment includes additionality: would the social or ecological benefit have occurred through a simpler system, conventional analytics, institutional reform, or direct investment?

The regenerative pathway also includes distribution and time. A data center may support global services while increasing local water stress. Automated climate-risk pricing may improve financial foresight and withdraw coverage from vulnerable communities. Precision agriculture may increase efficiency and deepen dependence on proprietary platforms. ProSocial AI asks whether ecological gains reinforce local agency, resilience, and fair access to resources.

Proposition 4

(regenerative and intergenerational). AI deployment will improve present and future quality of life when its verified ecological and resilience benefits exceed lifecycle costs, lower-impact alternatives have been considered, and benefits and burdens are fairly distributed. Effects will weaken or reverse when resource use, rebound, environmental injustice, or infrastructure dependency reduces the ecological and social foundations of future well-being.

5. Four Enabling Conditions

The pathways describe how value may be created. Four enabling conditions determine whether that value is likely to materialize and endure.

5.1 Double Literacy

Double Literacy combines human literacy with algorithmic literacy. Human literacy is the capacity to notice and interpret one's aspirations, emotions, thoughts, and sensations, together with values, biases, relationships, and vulnerability. Algorithmic literacy is the capacity to understand what an AI system does, what shapes its outputs, where uncertainty and incentives enter, how it influences attention and judgment, and when verification or human expertise is required.

The combination matters because technological knowledge alone does not secure agency. A person may understand that a model predicts likely text and still use it compulsively, accept flattering guidance, or outsource a decision that requires moral responsibility. Self-awareness without system knowledge leaves people vulnerable to opacity and automation bias. Double-literate users and professionals can pause, interrogate, compare, contextualize, and decide.

Double Literacy also applies institutionally. Organizations need a realistic understanding of their own goals, incentives, power, and capacity, alongside technical understanding of the system. Otherwise a procurement team may automate a flawed process, or leaders may treat vendor assurances as evidence of public value.

5.2 Meaningful participation

Quality of life is culturally situated and value-plural. People differ in how they understand dignity, care, independence, success, family obligation, risk, and a good future. Participation helps identify these differences before they become design failures. It also recognizes affected people as agents rather than data sources or recipients.

Meaningful participation has influence, continuity, and resources. Participants can shape the problem definition, acceptable uses, indicators, safeguards, and decisions following evidence. Inclusion at a late-stage consultation cannot repair a system whose objectives were fixed elsewhere. Participation should include people who face barriers to access, those likely to experience error, frontline workers, communities hosting infrastructure, and groups whose language or knowledge is underrepresented.

Participation also disciplines the term “prosocial.” Institutions cannot credibly define the good of others without processes through which those others can express priorities, dissent, and alternatives.

5.3 Contestability

Contestability is the practical capacity to question, challenge, correct, and seek remedy for an AI-influenced decision or environment. It extends beyond explanation. A person may understand why a system produced an outcome and remain unable to change it. Effective contestability requires a visible decision owner, accessible channels, timely human review, relevant evidence, protection against retaliation, and authority to provide remedy.

At the collective level, contestability includes independent audit, civil-society scrutiny, worker voice, research access, regulatory authority, and public reporting. It also includes reversibility. Institutions need

the technical and contractual ability to modify, suspend, replace, or exit a system. Dependence on proprietary infrastructure can turn formal oversight into an empty promise.

5.4 Proportionality

Proportionality aligns the intensity, autonomy, data use, cost, and ecological burden of an AI system with the importance of the need and the strength of evidence. It asks whether AI is suitable, whether a simpler intervention could work, and whether expected benefits justify foreseeable harms.

This condition prevents technological maximalism. Some quality-of-life problems arise from scarce staff, weak institutions, discrimination, insecure work, unaffordable housing, or inadequate public services. An AI interface may improve navigation while leaving the structural cause intact. Proportionality places AI within a portfolio of possible responses and protects attention and resources for institutional or social change.

6. The 4 x 4 Quality-of-Life Lens

The PAI-QOL model uses a 4 x 4 lens to prevent narrow evaluation. The four human dimensions are aspirations, emotions, thoughts, and sensations. They describe how quality of life is oriented, felt, interpreted, and embodied. The four levels are individual; community and institution; country and system; and planet and future generations. They describe where effects emerge, accumulate, and become governed.

Table 1 organizes these questions across the four human dimensions and four levels.

Table 1
The 4 x 4 ProSocial AI quality-of-life lens

Human dimension	Individual	Community and institution	Country and system	Planet and future generations
Aspirations	Does AI widen valued goals, perceived possibility, voice, and freedom to choose?	Does it support shared purpose, participation, and collective efficacy?	Does it align innovation with public priorities, inclusion, and long-term development?	Does it preserve options, ecological security, and a fair chance to thrive?
Emotions	Does use affect hope, anxiety, loneliness, dignity, trust, and belonging?	Does it strengthen care, reciprocity, psychological safety, and bridging ties?	Does it affect social cohesion, institutional trust, fear, stigma, or polarization?	Does it support solidarity with distant communities, non-human life, and future generations?
Thoughts	Does it strengthen understanding, judgment, creativity, and verification?	Does it improve shared knowledge, deliberation, professional learning, and local problem-solving?	Does it improve evidence use, policy learning, epistemic diversity, and public reasoning?	Does it deepen systems understanding, foresight, and recognition of ecological interdependence?
Sensations	Does it affect health, attention, fatigue, sleep, stress, accessibility, and embodied autonomy?	Does it alter workload, safety, care quality, public space, and exposure to harm?	Does it change population health, work intensity, service access, and infrastructure risk?	What are its energy, water, material, pollution, climate, and biodiversity effects?

The lens has two functions. Analytically, it reveals pathways that conventional performance metrics miss. A tutoring system may improve correct answers while increasing anxiety and reducing intellectual confidence. A public-service assistant may improve access at the individual level while creating national dependence on a foreign vendor. A climate application may improve forecasting while increasing local water stress. Governance-wise, the lens supports deliberation across disciplines. Psychologists, educators, clinicians, technologists, environmental scientists, public administrators, and affected communities can locate different forms of evidence within one structure.

The matrix does not imply equal measurement in every cell. Relevance depends on the use case. It creates a reasoned requirement to consider each domain and document exclusions. This feature reduces metric cherry-picking and helps identify displaced harms.

7. From Framework to Evaluation

7.1 The ProSocial AI Index as a dashboard

The ProSocial AI Index can operationalize the PAI-QOL model, provided it is treated as a multidimensional dashboard rather than a single score that hides trade-offs. Its purpose is to map, measure, monitor, and manage AI's effects.

Map establishes where AI is used, the need it addresses, the 4T choices, the people and environments affected, the institutional owner, and the decision points where human agency matters. **Measure** establishes a baseline and tracks outcomes across the four pathways and 4 x 4 lens. **Monitor** observes change over time, including model drift, user adaptation, complaints, skill effects, inequality, trust, and environmental load. **Manage** links evidence to decisions: redesign, restrict, strengthen participation, change procurement, add human support, pause, scale, or terminate.

A dashboard preserves distinct values that cannot be responsibly collapsed. A small improvement in convenience cannot be assumed to compensate for a serious rights violation. A national productivity gain cannot automatically offset local water insecurity. Thresholds and veto conditions may therefore be more appropriate than weighted averages in high-stakes domains.

Table 2 summarizes the core domains, questions, indicators, and evidence sources.

Table 2
Core PAI-QOL evaluation domains

Domain	Central question	Illustrative indicators	Key evidence sources
Agency and capability	Are people more able to understand, choose, learn, and act after using the system?	Perceived autonomy; decision comprehension; skill retention; option diversity; verification behavior; appropriate reliance; ability to refuse or exit	User studies; performance tests; longitudinal skill assessment; interaction logs; interviews
Relational quality and social capital	Does the system strengthen reciprocal support, trust, bridging ties, and accountable care?	Loneliness; belonging; relational time; reciprocity; bridging and linking ties; collective efficacy; referral to human support	Well-being surveys; social-network analysis; ethnography; service data; community feedback
Institutional public value	Does AI improve access and responsiveness while preserving fairness, dignity, and recourse?	Service completion; waiting time; error distribution; appeal success; explanation quality; professional discretion; trust; complaints	Administrative data; audits; mystery-user studies; grievance records; worker and citizen panels
Regenerative and future value	Do ecological and resilience gains justify lifecycle burdens and preserve future options?	Energy; water; carbon; materials; hardware life; rebound; environmental additionality; local burden; resilience outcomes	Lifecycle assessment; vendor disclosure; infrastructure data; environmental monitoring; scenario analysis
Distribution and justice	How are benefits, harms, voice, and burdens distributed?	Access; affordability; subgroup performance; language coverage; disability inclusion; community burden; participation influence	Disaggregated data; accessibility testing; participatory evaluation; distributional impact analysis
Governance integrity	Can the system be understood, challenged, corrected, and stopped?	Named owner; auditability; human-review capacity; response time; remedy; contract rights; incident reporting; exit readiness	Governance records; contracts; audit trails; red-team reports; regulator and civil-society review

7.2 Evaluation design

Credible evaluation requires more than post-deployment satisfaction surveys. Four design choices are particularly important.

First, studies need a **counterfactual**. The comparison may be an existing service, a lower-technology intervention, professional support, or no intervention. This reveals whether AI adds value and whether another approach delivers similar benefits with lower risk or resource use.

Second, studies need temporal and distributional resolution. Immediate task success, short-term affect, medium-term behavior, and long-term capability can move in different directions. Average effects can

also hide harms by language, disability, income, gender, age, location, education, or institutional status. Repeated-measures and longitudinal designs should therefore be combined with pre-specified subgroup analysis, adequate samples, and attention to intersectionality.

Third, evaluation needs mixed methods. Quantitative outcomes can estimate magnitude and distribution. Qualitative research can reveal meaning, dignity, fear, changing practices, and unanticipated mechanisms. Participatory methods help identify outcomes that affected communities consider important.

Fourth, evidence must lead to governance consequences. Monitoring without decision thresholds becomes observation. Before deployment, institutions should define conditions for escalation, redesign, restriction, and termination. These conditions should include social and ecological outcomes alongside technical incidents.

8. Applied Test Arenas

The framework becomes useful through focused application. Three arenas illustrate how the pathways and enabling conditions guide research and practice.

8.1 Learning and education

AI tutoring and generative assistance can provide explanation, translation, feedback, adaptive practice, and support for teachers. Pro-people outcomes include access, comprehension, learner confidence, disability inclusion, reduced administrative burden, and stronger teacher-student relationships. Pro-potential outcomes include curiosity, independent reasoning, creativity, and the ability to use AI with judgment. Pro-planet considerations include the resource intensity of continuously generating individualized content relative to educational value.

An education study guided by PAI-QOL would measure learning gains together with self-efficacy, cognitive effort, source verification, skill retention after assistance is removed, teacher workload, relational time, and inequalities in access. It would compare answer-generating interfaces with scaffolded systems that ask learners to attempt, explain, and revise. The key causal question is whether assistance expands competence or merely improves the visible product.

Double Literacy belongs in the intervention rather than an optional orientation session. Students need to understand model limitations and their own tendencies toward avoidance, overconfidence, comparison, or dependence. Teachers need sufficient professional agency to decide when AI supports pedagogy and when it disrupts the learning process. Contestability includes a student's ability to challenge AI-supported grading or detection. Participation includes teachers, learners, parents, disability experts, and communities whose language or cultural knowledge enters the system.

8.2 Health, care, and social connection

AI can support documentation, care navigation, translation, patient education, triage, monitoring, and communication. It can also simulate companionship and emotional support. Quality-of-life evaluation must therefore distinguish clinical effectiveness, subjective experience, relational continuity, and institutional responsibility.

A ProSocial AI care tool would help people understand options, prepare questions, follow treatment, and reach appropriate human support. It would preserve the accountability of professionals and organizations. Measurements could include symptom or functioning outcomes, patient understanding, perceived dignity, clinician burden, continuity, errors, escalation quality, trust, loneliness, and changes in human contact.

The relational pathway is central. A conversational system may help a person articulate distress before speaking with a clinician or family member. It may also become the easiest available relationship, particularly where services are scarce. The design should make healthy boundaries visible, avoid claiming human feeling, and detect situations that require qualified support. Research should separate momentary relief from changes in social behavior and network quality over months.

8.3 Community resilience and climate adaptation

Communities face heat, flooding, pollution, food insecurity, and disaster risk through unequal infrastructures and resources. AI can integrate environmental data, identify vulnerability, improve warning, support emergency logistics, and translate technical information. These applications connect all four pathways: individual agency to act, community coordination, institutional responsiveness, and ecological resilience.

A PAI-QOL evaluation would begin with local knowledge and priorities. It would ask whether warnings reach people in usable languages and formats; whether communities trust the source; whether residents can correct inaccurate maps; whether vulnerable groups receive resources; whether emergency institutions respond; and whether the AI infrastructure creates material burdens elsewhere. Social capital is both a mediator and an outcome. Strong networks help communities act on information, while participatory systems can strengthen linking ties with authorities.

This arena also reveals why technological accuracy cannot carry the whole intervention. A precise flood prediction provides limited quality-of-life value where residents lack transport, safe shelter, insurance, or confidence in authorities. ProSocial AI should therefore be embedded in institutional commitments and material capacity.

9. Failure Modes and Safeguards

A strong framework must clarify how it can fail. Four failure modes deserve particular attention.

9.1 Prosocial washing

The term “prosocial” can become a reputation device. Firms and institutions may point to benevolent use cases while concealing business models based on extraction, engagement, or dependency. Safeguards include public definitions, outcome evidence, independent evaluation, disaggregated reporting, ecological disclosure, and restrictions on claims. ProSocial status should remain provisional and use-case specific.

9.2 Paternalistic optimization

Designing for well-being can license intrusive steering when institutions define what people should value. Personalized persuasion may be presented as support. The safeguards are pluralism, participation, user-defined goals, limits on manipulation, and meaningful refusal. The capability approach is especially useful because it values real freedom and reasoned choice rather than compliant behavior.

9.3 Agency and relationship substitution

Convenience can gradually replace practice, professional judgment, and human contact. The risk grows when systems are always available, socially responsive, integrated across tasks, and rewarded for engagement. Safeguards include graduated assistance, skill-retention testing, friction for high-stakes delegation, human-contact pathways, usage reflection, and business models that do not monetize dependency.

9.4 Burden displacement

AI can shift costs across people, places, and generations. Automation may improve customer convenience and intensify hidden labor. Environmental optimization in one region may rely on water or minerals extracted elsewhere. Risk scoring can reduce institutional uncertainty and increase insecurity for individuals. Safeguards require lifecycle and value-chain assessment, distributional analysis, labor standards, local consultation, and transparent treatment of uncertainty.

10. Research Agenda

The PAI-QOL model generates a research agenda with four priorities.

First, research should test the **conversion pathways**. Experimental and quasi-experimental studies can examine whether autonomy, competence, relational support, or institutional responsiveness mediate quality-of-life effects. Multilevel models can test whether organizational practices, governance quality, and social capital moderate individual outcomes. The four propositions provide an initial structure.

Second, research should develop and validate **measures of Double Literacy and appropriate reliance**. Current AI-literacy measures often emphasize knowledge or confidence. A fuller instrument should assess verification, uncertainty recognition, understanding of incentives, values awareness, emotional self-observation, ability to identify inappropriate delegation, and capability to seek human support. Behavioral measures are needed alongside self-report.

Third, research should examine **dynamic and cumulative effects**. Longitudinal studies can track the movement from experimentation to integration, reliance, and addiction; the development or loss of skill; changes in trust; and the evolution of human networks. Research on AI companionship, education, and professional decision support particularly needs designs that extend beyond brief exposure.

Fourth, research should integrate **planetary and distributional accounting** into quality-of-life evaluation. This includes lifecycle footprints, rebound, local water and energy conditions, e-waste, labor, and the geographic distribution of benefits and burdens. Comparative studies should examine whether smaller, local, or task-specific models deliver similar social value with lower resource intensity. Global South contexts require particular attention because imported systems can create linguistic, institutional, infrastructural, and epistemic dependencies while overlooking local innovation.

Cross-cultural research is essential throughout. Aspirations, relational norms, institutional trust, and acceptable trade-offs vary. The framework offers common domains while leaving indicators and thresholds open to contextual definition. This balance supports comparison without imposing a single model of the good life.

11. Discussion

The PAI-QOL model contributes to quality-of-life research by specifying how a general-purpose technology may be converted into multidimensional human and planetary outcomes. It complements Höfer's (2026) humanistic account by providing mechanisms, enabling conditions, propositions, and measurement domains. It complements Shi and Sirgy's (2026) governance finding by opening the institutional “black box”: governance quality operates through participation, professional capacity, contestability, procurement, monitoring, and enforceable responsibility. It also connects the emerging evidence on algorithmic harm and companionship with a broader theory of relational and capability effects.

The model contributes to AI governance by moving evaluation from risk containment toward demonstrable contribution. Responsible and trustworthy AI frameworks remain foundational. ProSocial AI asks an additional question: after safety, legality, and technical performance have been addressed, what evidence shows that the system improves lives, relationships, institutions, and future conditions? This question discourages the assumption that adoption equals progress.

The framework also reframes hybrid intelligence. Human-AI collaboration is frequently described in terms of complementary performance. PAI-QOL defines a stronger goal: the interaction should leave people, communities, and institutions more capable of understanding and directing their future. Hybrid intelligence reaches its highest value when artificial capacity amplifies natural intelligence without hollowing out the human agency needed to govern it.

For practice, the central implication is sequencing. Institutions should begin with a quality-of-life need, affected groups, and a plausible mechanism. They can then determine whether AI is suitable, shape the

4Ts, establish enabling conditions, define measures and thresholds, and deploy in stages. This sequence differs from acquiring a tool and searching for use cases. It is slower at the beginning and more likely to prevent costly lock-in, harm, and loss of trust.

For policy, the model supports quality-of-life impact assessment, public procurement requirements, AI-literacy strategies, environmental reporting, and national well-being dashboards that include AI exposure and capability. Existing risk-based regulation can be strengthened by social and subjective outcomes. Legal compliance creates a floor. Public value and quality of life provide the direction.

The model has limitations. It is conceptual and requires empirical validation. Its domains can conflict, and there is no neutral formula for resolving every trade-off. Quality of life remains culturally plural. Environmental data from AI providers are often incomplete. Causal attribution is difficult because AI is embedded in wider organizational and social changes. The 4 x 4 lens may appear expansive, and practical assessment will require careful scoping. These limitations create a research program rather than invalidate the framework.

A further limitation concerns language. “ProSocial AI” may imply that the system itself possesses social intention. The term is used here as a property of sociotechnical design, deployment, and governance. Responsibility remains human and institutional. AI can support prosocial processes; it cannot assume moral accountability for them.

12. Conclusion

AI is becoming part of the environment in which quality of life is formed. Its effects arise through the interaction of models, people, relationships, institutions, and planetary systems. ProSocial AI offers a direction for that interaction: pro-people in present experience and dignity, pro-planet in ecological responsibility, and pro-potential in the capabilities and options preserved for the future.

The PAI-QOL model identifies four routes from AI to quality of life: agency and capability, relational and social capital, institutional and public value, and regenerative and intergenerational pathways. Double Literacy, participation, contestability, and proportionality determine whether these routes remain open. The 4T architecture embeds purpose across the lifecycle, while the 4 x 4 lens protects evaluation from narrow metrics. The four propositions invite empirical testing.

The standard is demanding by design. A system earns the description “prosocial” through evidence that people are more able, relationships and institutions more trustworthy, benefits more fairly shared, and ecological foundations more secure. This approach turns quality of life from an aspirational slogan into a criterion for technological direction. It also restores a central fact of the hybrid future: human beings remain responsible for deciding which capacities technology should amplify, which dependencies society will accept, and which future becomes possible through the choices made today.

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Author Contribution

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Ethical Declaration

This article does not contain any studies with human participants performed by any of the authors.

No specific consent was therefore required.

Data availability

Yes. All data covered is documented in the references in this article.

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Figures

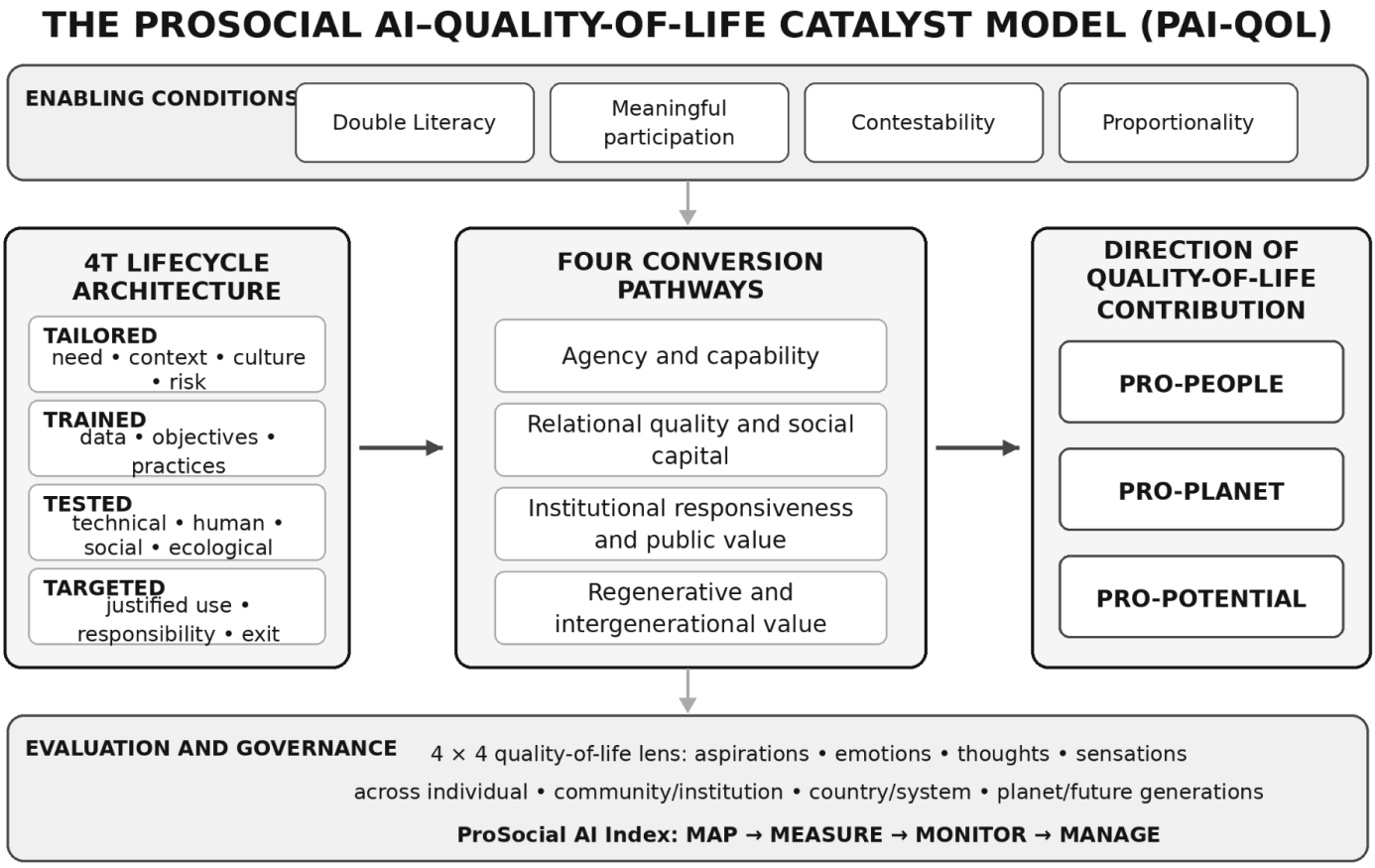


Figure 1

The ProSocial AI–Quality of Life Catalyst Model (PAI-QOL).