Technology, Artificial Intelligence and Service Innovation for Sustainable Development: A Service Ecosystem Perspective

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ABSTRACT

Artificial intelligence is being integrated into enterprises as an integral component rather than a separate technology. This style offers opportunities for prediction, personalization, automation, collaboration, and learning but also involves redistributing agency, information, risk, and value, across firms, customers, employees, forums, communities, and ecosystems. Research on AI-enabled tools, innovative workflows, co-creation of value, and sustainable development has yet to fully characterize them. This article aims to understand how innovative AI-based tools can contribute to sustainable development by providing a general perspective that does not necessarily imply the desirability of adopting AI technologies. An integrative review and qualitative coding were conducted on 39 empirical and referenced papers. The integrated New Enterprise Process Action Framework shows how collaboration, co-development and collaborative, and co-learning activities at different levels can be accomplished with the help of AI capabilities. This study identifies six key drivers of value-added collaboration and AI in the workplace: AI capabilities, data quality, human judgment, actor collaboration, social design, and insight. In addition, the analysis incorporates values validation systems driven by isolation, bias, opacity, surveillance, regression effects, automation, cybersecurity threats, and statistical artifacts. The paper offers a perspective on how innovative uses and AI can be used to deliver lasting economic, social and environmental benefits. It is argued that sustainable operational innovation with AI requires biologists to engage with each other's data and take advantage of synergies and apply service concepts to meet specific performance indicators. Ecosystem managers should take advantage of the feedback mechanisms to update operating system models, platforms, and AI technology principles. The article provides an analysis of the concepts, strategies, and leadership to create AI-enabled services that maintain long-term value for customers, employees, and ecosystems.

Keywords: artificial intelligence; service innovation; service ecosystems; service-dominant logic; sustainable development

1. Introduction

Artificial intelligence (AI) has moved into applications that are not specific testing tools but rather a broad range of technologies. Recommendation algorithms change consumption patterns; chatbots transform customer interactions; predictive algorithms migration maintenance and logistics; computer vision enhances analysis and industrial analysis; and generative algorithms participate in scientific work. These technologies are embedded in work processes, modifying not only specifics, but also user data, resource integration, decision logic, and value-sharing strategies. In this case, the AI raises a service-system issue before the program query. The consequences extend to organizational and institutional changes, affecting customers, employees, suppliers, regulators, ecosystems and communities.

Job search unlocks an important perspective in this transition. Task control theory views tasks as the appropriation of resources for consumption and places value based on context, experience, and cooperation, rather than inherent characteristics of a product (Vargo & Lusch, 2004; 2008). The enterprise and ecosystem role further views this alignment as part of a larger network of resource system organizations, where interactions take place in highly self-organizing environments containing diverse resource management organizations (Vargo et al., 2015). In this sense, innovation can be viewed as a process that takes advantage of new combinations of resources, as well as establishing, stabilizing, or restructuring norms that allow the emergence of new practices (Lusch & Nambisan, 2015; Koskela-Huotari et al., 2016). In this view, artificial intelligence can accelerate and expand the integration of resources, while simultaneously risking the strength of certain norms.

The development of sustainable solutions poses a complex analytical problem. An intellectual property enterprise can hurt a company's business costs, while exacerbating output, increasing energy, or putting employees and communities at risk. In contrast, an optimal model for energy, waste, mobility, health, or agricultural landscapes may simultaneously advance multiple Sustainable Development Goals (SDGs) but generate a new collection of data and technical knowledge. According to Vinuesa et al. (2020), AI can contribute to most of the SDGs, but also hinders progress for some, while Nishant et al. (2020) argue that AI-driven programs for sustainability should be concerned not only with good systems but also with problems. Thus, we need to consider how innovations in services relate to various outcomes across economies, societies, and ecosystems, and consider indirect and long-term consequences.

All three contribute to this post. First, in many ways, research on AI-in-service focuses on the relationship between a firm and its customer. Focusing on automation, robots, personalization, and customer experience, literature gives limited attention to public institutions, supply chains, communities, and ecosystems (Huang & Rust, 2018; Wirtz et al., 2018). Second, when it comes to sustainability, literature typically lists potential areas where AI can be useful while providing little analysis of the operational and governance mechanisms through which value is co-created and sustained. Third, technology is often viewed only as an art, whereas in practice algorithms can make choices, make recommendations, negotiate, and modify their behavior, thus modifying relationships between different parties. The paper aims to develop a framework that will account for "responsibility" not only for companies and customers, but also for algorithms within enterprises.

The paper addresses two research questions:

RQ1: Through which multilevel mechanisms does AI enable or inhibit service innovation for sustainable development?

RQ2: Which governance practices align AI-enabled value co-creation with economic, social, and environmental outcomes across a service ecosystem?

To answer the research questions, the study synthesizes the literature that uses qualitative coding. Specifically, there are 39 articles analyzed through the micro-, meso-, macro- and meta-levels of AI-informed co-production of healthcare professionals, coming from Barile et al. (2020) in the. These four levels are reinterpreted according to how effectively a productive service proposal recognizes need, users, sustainability, and data constraints at the micro level; how partners contribute mutual information, knowledge, and operational inputs and outputs at the meso level; how integrated work affects health, distributional effects, environmental regulations, and the macro level of meeting sustainability development objectives; and how patterns themselves, actor roles, protections, and social norms are revised in light of the evidence that emerges at the meta level.

The paper makes four contributions. First, it connects AI usage research with a sustainable development-enabled service-ecosystem account. Second, it distinguishes four AI roles: instrument, facilitator, mediator and boundary agent. Third, it introduces the destruction of conflicts of interest into the same system as the creation of conflicts of interest, making risk structural (rather than exogenous). Finally, it refines the framework into theoretical statements for empirical evaluation, making the framework more analytical with quantifiable indicators. The result is a conceptual paper intended to inform prospective case studies, surveys, comparative ecosystem research and longitudinal evaluations.

2. Theoretical Foundations

2.1 Service-Dominant Logic And Service Ecosystems

Entrepreneurial philosophy has shifted the emphasis from goods as the basic unit of exchange to the idea of work as the application of skills for the benefit of others (Vargo & Lusch, 2004). Furthermore, its recent findings have shown that both social and economic actors contribute through their use of resources and that value is determined by its use and content (Vargo & Lusch, 2008). Thus, customers are no longer passive recipients, combining a company's goals with their own skills, time, contacts, information, equipment, and social resources. Such an approach is particularly applicable to digital services, where the success of a particular model depends on how one interacts with the platform and provides feedback.

Entrepreneurial ecology refers to a highly self-organizing system of combinations of resources connected by social arrangements through which value is exchanged (Vargo et al., 2015, 2017). These institutions include rules, contracts, regulations, professional norms, routines, categories, and institutional arrangements that reduce uncertainty in certain practices by enacting them. At the same time, institutions may limit innovation by enacting policies, routines, or other types of documented practices that favor established practices over other strategies. Consequently, innovation can be conceptualized as a process that goes beyond the development of new applications or algorithms but also involves changes in the integration of resources and the social arrangements that shape it (Lusch & Nambisan, 2015; Koskela-Huotari et al., 2016).

A lifestyle perspective helps prevent three downgrades. First, it avoids diminishing returns to the corporation. For example, a predictable maintenance service may require machine information from a customer, engineering expertise from a manufacturer, a cloud platform, an interconnection provider, maintenance services, insurance plans and regulatory clearance. Second, it avoids reducing innovation to adoption. The same algorithm can produce different effects for different incentive settings, user actions and different accounting regimes. Third, it allows for more time and space.

Barile et al. (2020) proposed a typology of work-related system operations consisting of micro, meso, macro, and meta levels. Their framework links collaboration, collaboration, collaboration, and co-learning to achieve sustainable integration. The power of architecture lies in its ability to connect operational actions with local outcomes. However, modern artificial intelligence has specific characteristics that need to be incorporated: feasible output, model opacity, flexibility, large databases, near-zero marginal cost of connectivity, and reliance on object computing infrastructure. In doing so, the authors miss new changes in the speed and rate of error propagation.

Research into digital-age service innovation and technology-enabled value co-creation further demonstrates that such outcomes are contingent on configurations of actors, resources, and practices beyond technology (Barrett et al., 2015; Breidbach & Maglio, 2016).

2.2 AI As Resource, Capability, Mediator, And Bounded Agent

AI is not the only technology. In applications it is applied to machine learning, natural language processing, computer vision, management, robotics, and exchange models. The solutions provide different capabilities that can be combined. Perceptive AI recognizes patterns in images, gestures, speech or actions. Predictive AI forecasts future opportunities, risks, demands, or shortages. Generative AI creates text, images, designs, programs or data. A commanding AI indicates or performs an action that involves constraints. A new tool can be used with greater capacity, and the complexity of governance changes as autonomy and impact increase.

Early operational research focused on technology as primarily an active resource that acts on other resources or enables new forms of interaction (Akaka & Vargo, 2014). It is still the case that an algorithm is only effective when combined with data, domain knowledge, organizational behavior and user skills. Yet AI can also enable discovery, prioritize issues, frame choices, and initiate action. Huang and Rust (2018) distinguished mechanical, analytical, cognitive, and empathic processing tasks and stated that the transition of AI tends to move from habitual to complex cognitive processes. Huang and Rust (2021) further tie AI capabilities to business strategies. These stories explain why the role assigned to AI should be transparent rather than implicit.

The paper describes four types of roles. First, AI is a tool, which performs limited analytical or automated functions under the direct control of a human operator. Second, AI acts as an assistant, which augments the worker or user's ability by suggesting options, providing explanations, or drafting text. Third, AI acts as an intermediary, which matches actors, allocates and distributes attention, creates personalized offerings, or designs interactions. Finally, AI is a bounded agent, which makes choices or acts within a limited set of rules of authority, supervision, and augmentation. The categories are intended to describe modes of governance rather than a question of consciousness. A human operator cannot delegate accountability to an AI model.

Organizations and partners who design and adopt technology remain responsible for its choices, operating conditions, and expected impacts. The automation-augmentation paradox best applies to this argument. Organizations are interested in automating processes to achieve scale and standardization, but effective AI requires extensive human input in the form of knowledge, judgment, and relevant information (Raisch & Krakowski, 2021). In other words, too much automation eliminates the opportunity to discover gaps in the model's logic or unexpected requirements. On the other hand, too much reliance on manual review can eliminate the cost-effectiveness and speed benefits of using such a service. Therefore, designing a service around AI capabilities involves dividing tasks according to uncertainty, importance, explainability, and user preferences, while considering the benefits to each party.

AI skills are also different from software availability. Organizational AI capabilities are determined by access to data, technical infrastructure, computational expertise, domain knowledge, governance mechanisms, and the ability to influence and redesign processes. Mikalef and Gupta (2021) link AI capabilities to creativity and organizational performance, whereas Jöhnk et al. (2021) identified logistical factors rather than technological resources. Depending on the ecosystem, these resources can be distributed among various actors in the innovation environment. To achieve sustainability, it is critical to ensure that complementary actors are willing and able to combine their resources without relying on any of them to the detriment of the others.

Broader assessments of AI's organizational opportunities and challenges also show why an assigned AI role must be explicit rather than implied (Davenport et al., 2020; Dwivedi et al., 2021).

2.3 Service Innovation As Institutional And Relational Change

Lusch and Nambisan (2015) define new jobs in terms of resource renewal processes that bring valuable new resources to users. Digital technologies reduce friction that can lead to fragmented innovation (Nambisan et al., 2017). AI improves such processes by recognizing patterns, suggesting alternatives, and learning from operational process controls. It can enhance an existing experience, inspire a results-based offering, develop a platform, or redesign the entire ecosystem.

Four types of new use cases enabled by AI can be identified. Process innovation increases the speed, quality, availability, or resources of a given service. Innovation transforms understanding, access, or participation in an activity. New business models involve changing economic logic, risk allocation, ownership, or the mix of products and services. Organizational innovation modifies rules, employee roles, or accounting standards. The first two types are usually seen at the micro level, while the other two require meso- and macro-level analysis.

Digital servitisation exemplifies the dynamics of the issue. Manufacturers are adding integrated features, estimates and service contracts. AI can identify failure, improve performance, extend asset life, and make consensus based on outcomes. Sjödin et al. (2023), for example, show how reasoning, forecasting and legal skills are affected by the new business environment. However, the outcome of sustainability depends on the design of the contract: a provider who is rewarded with longevity and life expectancy can reduce emissions; which trades solely on the volume of trade could use the same interpretation of power to stimulate demand. Technology does not determine the social concept in which it operates.

AI also transforms the cooperation of interests in employment relationships. Discussion systems could enhance access while reducing research costs, while recommendation systems could help solve problems. Empirical and review studies associate AI with customer engagement and value creation (Chandra & Rahman, 2024; Behera et al., 2024). At the same time, the mediated encounter could be manipulative or exclusionary when the personalization is not transparent, the data extraction is uncompensated, and/or access to the human is lacking. Thus, a full account of the value-sharing process must include destruction of values: relational processes in which resources are wasted, value potential is reduced, or one person’s value incurs unpaid costs for the other.

Recent emphases point to the potential of AI for product–service innovation, making it a distinct and growing area of research (Naeem et al., 2025). Technology, employees and customers also shape interrelated roles in contemporary work relationships (Larivière et al., 2017).

2.4 Sustainable Development and The Double Materiality Of AI

Sustainable development is the integrated consideration of economic, social and environmental issues. Sustainable marketing research draws attention beyond tangible benefits for customers and businesses to include society and community (Bocken et al., 2014). Similarly, circular economy research indicates the need to focus on resource recovery and recycling rather than solely on efficiency (Geissdoerfer et al., 2017). AI-enabled services, i.e. faster or cheaper delivery, are not sufficient arguments for sustainability.

The sustainability implications of AI users involve two-way issues. AI for sustainability refers to the impacts of using AI to improve energy, mobility, food availability and quality, health, education, biodiversity, disaster prevention, circulation, and public transport. Sustainable AI refers to the conditions of energy, water, fuel, manpower, data and governance required to develop and operate AI applications. Van Wynsberghe (2021) suggests the need to consider both directions. Two technical problems arise; ecosystems must consider the impact of AI tools on sustainable development, as well as the impact of social and environmental impacts on the viability and legality of the AI industry.

Vinuesa et al. (2020) classified the enabling and hindering effects of AI across the Sustainable Development Goals (SDGs). Positive support includes resources, supervision, personalization, and cognitive development. However, the authors identify opportunities for inequality, with too much power, surveillance, outsourcing, and demands for accountability as major risks. Climatological analyzes add an important perspective: Kaack et al. (2022) suggest assessing the impact of machine learning on climate through functional, social, and statistical effects. Schwartz et al. (2020) call for empirical research on AI, while Strubell et al. (2019) accounted for the energy and political costs of large-scale model constructions.

Sustainability analyzes of AI distinguish between direct effects, potential and environment. The former involves the power and consumption of AI itself; the latter two reflect the transformative forces that shape the given activity, such as behavioral changes, markets, and distributional outcomes. Direct transportation management can lead to higher overall employment and new unemployment through displacement effects. Similarly, the digital public service may fail to serve citizens who lack communication or language translation or access to education.

The sustainability effects of AI systems cut across countries, sectors and functions, and studies show that the social and practical benefits are greater than just adoption (Nahar, 2024; Nasir et al., 2023; Pigola et al., 2021).

2.5 Responsible AI as ecosystem governance

Ethically valid AI principles focus on efficacy, impartiality of action, autonomy, depth, responsiveness (Floridi et al., 2018). Dialogue can be attentive, modest, show respect, and use if your promise is repetitive (Jobin et al., 2019). These are important but the principles are not clear (Mittelstadt, 2019). Agencies do do must responsibility, rights allocation, back, truth, dispute, solutions, procurement flexibility, and flexibility.

Competition is also a social phenomenon. A bet variable that is important to the model may be too high for a bond that is challenging the decision. Rai (2020) has entered the AI way of how with man, ku tie you with manual needs. Within the enterprise environment, what should be prioritized and established if it is feasible: feasible, need feasible.

So, the responsibility of AI is not full compliance but make it fully in, work souls for souls, allocate tasks, standardize, and learn. Peace should be fully utilized. Governance right while on the waste as a ability to fully sustain therefore avoiding delay costs and cause action within your fully qualified assets.

3. Methodology

3.1 Review design

The study will involve an integrated literature review, with future qualitative coding. The choice of an integrated study design indicates that the research question seeks to examine the concepts of entrepreneurship, new applications related to digital and AI, sustainable development, business cycles, and AI responsibilities. These currents employ a variety of different concepts and methods, without the question itself placing any special connection between them beyond the need for external recovery. A purely statistical approach is inappropriate, due to the large number of variables and the interdependence of both dependent variables, making it impossible to combine the results into a single effect size estimate.

On the other hand, this study does not intend to test specific hypotheses. Therefore, a comparative, descriptive approach was chosen, based on the database of Barile et al. (2020 year). The article provides a comprehensive overview of transforming workplace ecosystems through technology integration, identifying the key components of micro-, meso-, macro- and meta-levels, as well as the mechanisms of integration, collaboration, collaboration, and co-learning. From this point on, this study has identified areas of AI-informed research that would benefit from a detailed assessment of capabilities, threats, stakeholders, and governance strategies. The foundations of the tools and social literature were then incorporated to ensure conceptual coherence, while the focus of inquiry guided the search for recent articles on key AI and sustainability science strategies and outcomes.

3.2 Source selection

Final evidence was generated from 39 publications to ensure internal consistency and meet the limited scope. Sources were selected using an objective theoretical approach and should not be considered a complete research report. Each theme had to make a significant contribution in at least one of five areas: workplace ecosystems and co-creation of value; new digital or AI-enabled workflows; AI potential or adoption; AI and sustainable development; or responsible and sustainable AI. The first step consisted of peer-reviewed journals, with publication data and DOI linkages for evidence analysis. Older sources of higher conceptual status in the framework were included.

The procedure consisted of four steps. First, the structure and claims of the database were reviewed. Second, the search used the title and keywords: “artificial intelligence,” “innovation,” “workplace ecosystem,” “co-creation of value,” ‘sustainable development,’ ‘circular,’ and ‘AI responsibility.’ Third, candidates were evaluated for direct relevance and conceptual integration. Fourth, the bibliographic references and DOI specifications of each source were checked against the publisher’s database or DOI. Index. The evidence file that can be accessed with this theme contains both coding and descriptive details for each source and should support evidence reproduction.

Figure 1 shows how framework mapping and purposive source selection feed structured coding, constant comparison, negative-case integration, and final theory development. The result is that it represents the method used in this conceptual article, not a field-data collection process.

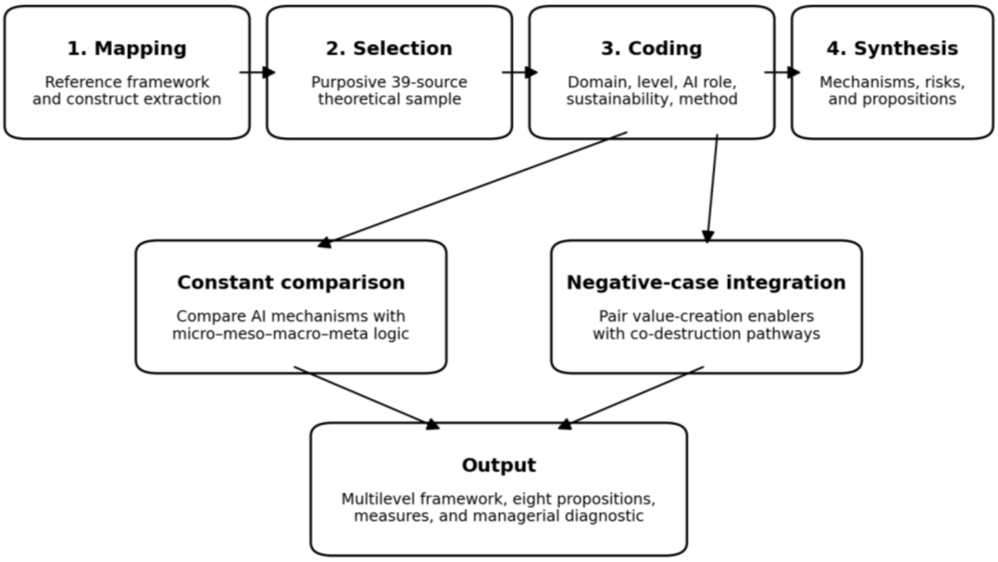

Figure 1. Integrative review and theory-building procedure

3.3 Coding framework and analysis

Each transcript was coded according to five factors. The first concerns the area of knowledge to which the article contributed most significantly. It could be biological theory, work with AI, organizational skills, sustainability practice, or governance and risk. The second factor was the extent to which lifestyle affects the work described in the manual. It can be micro, meso, macro, metal or multilevel. The third was the role of AI which was closely related to the findings of the article. It can be a device, a helper, a mediator, a boundary agent, or a non-specific role associated with foundation theory. The fourth factor was the sustainability framework considered in the book. It can be economic, social, environmental, sustainable, or related to art theory. Finally, the fifth section described the research methods used in the paper, such as conceptual, review, qualitative, quantitative, mixed methods, or method-analytic methods.

The coding process was interpretative and therefore less dependent on theoretical constraints. Nevertheless, to be consistent with the hierarchical narrative strategy, each article was assigned to a single category as the primary contributor to the core evidence. This allowed the research team to avoid double counting, while emphasizing the broader role of each journal. The figures presented in this research do not reflect the overall contribution of each article to the field. Instead, they show the distribution of evidence that has been used to prepare the study conclusions.

The analysis followed the usual peer-to-peer method. In particular, the methods described in the articles are like those of Barile et al. (2020) on AI-specific conditions. Each method was combined with similarities presented in other papers to form six interconnected patterns. These included strategies, resources, actors, data management, institutional regulation, and training and strategic actions. Negative and risk-related strategies were combined to identify mechanisms and patterns of conflict of interest. Finally, the framework was validated through comparative theoretical and comparative tests, using theoretical statements and indicators.

Table 1 shows the procedure supports integrative theory development. The result is that it is transparent and reproducible at the source-coding level, but it is not presented as an exhaustive systematic review or meta-analysis.

Table 1. Review protocol and analytical decisions

Step in Review Process	What Was Done in This Step	Why This Step Was Needed
Framework mapping	Extracted micro, meso, macro, and meta levels and their co-innovation practices from the reference framework	Used the existing framework as the foundation of the study
Purposive selection	Selected 39 relevant and verifiable foundational and focal publications	Maintained depth while staying within the reference limit
Dominant coding	Assigned each publication a main domain, ecosystem level, AI role, sustainability focus, and research method	Created clear and comparable evidence summaries
Constant comparison	Compared AI mechanisms, enabling conditions, and risk pathways across studies	Developed cross-level explanations
Theory output	Developed the framework, propositions, and measurement indicators	Prepared the model for future empirical testing

4. Descriptive Evidence Map

The evidence map is designed for two purposes. First, it was intended to illustrate the philosophy of the selected sources and to visually demonstrate where the proposed framework is based on established assumptions and where it makes use of emergent, emergent findings. Second, the annual report shows a base of operations science, followed by a rapid increase in AI, sustainability, and governance-related courses starting in 2018. This trend is expected because modern operations-management theory predates AI practice today.Figure 2 shows seminal service research supplies the conceptual foundation, while AI, governance and sustainability studies expand rapidly from 2015 onward. The result is that period counts describe the selected corpus only.

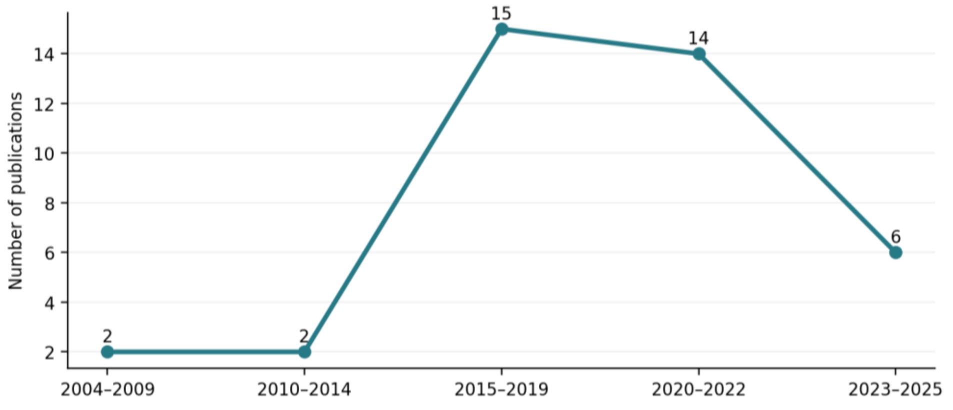

Figure 2. Temporal profile of the selected evidence base

The domain pivot suggests that the set is deliberately poised between service-ecosystem foundations, AI-enabled service studies, sustainability research, organizational capability, and responsible-AI governance. No frequency should be read as field-wide ubiquity. Rather, the profile shows that the synthesis does not present sustainability as a minor addendum to technology literature. Governance and environmental constraints are afforded explicit representation.

figure 3 shows sustainability and ecosystem theory are deliberately represented alongside AI-enabled service and governance research, preventing the framework from being dominated by technical adoption studies. The result is that sustainability and ecosystem theory are deliberately represented alongside AI-enabled service and governance research, preventing the framework from being dominated by technical adoption studies.

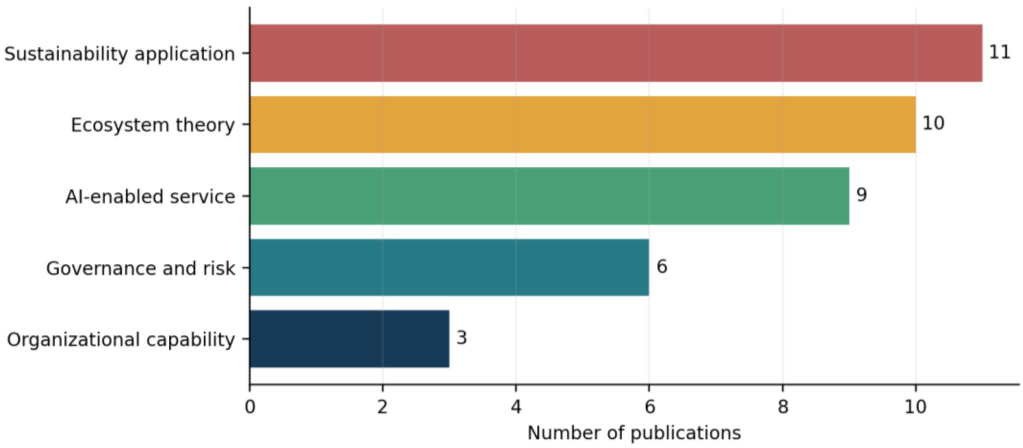

Figure 3. Evidence based by primary knowledge domain

The ecosystem-level pivot reflects the tendency that most previous studies have focused on the micro-level and multilevel group. Micro-level studies examine customer encounters, user activity, adoption, configuration, or vertical performance. Multilevel and macro-level studies dominate in SDGs, ethics, climate impacts, and agency analysis, while cross-sectoral studies on peer-to-peer data, partner governance, and inter-organizational learning remain underdeveloped. This trend is explained by the fact that many AI services rely on open data and resources shared across organizational boundaries.

Figure 4 shows micro and multilevel work dominates, while meso-level partner arrangements and meta-level learning are comparatively sparse. The result is that this distribution motivates the paper's emphasis on reciprocity and reflexive orchestration.

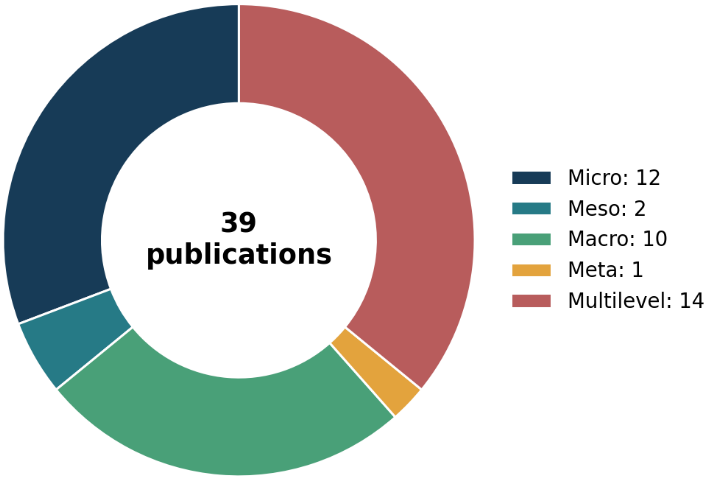

Figure 4. Evidence based by dominant ecosystem level

The sustainability-orientation chart shows why an integrated framework is needed. Service and capability studies often use economic or enabling outcomes, whereas AI-for-sustainability publications address social, environmental, or combined outcomes. Triple-bottom-line analysis remains less common than positive application narratives. The framework developed below treats economic viability as necessary but prevents it from standing in for sustainability.

Figure 5 shows economic and combined sustainability concerns are well represented, but environmental studies remain fewer. The result is that "Enabling theory" identifies sources that define ecosystem mechanisms without claiming a sustainability outcome.

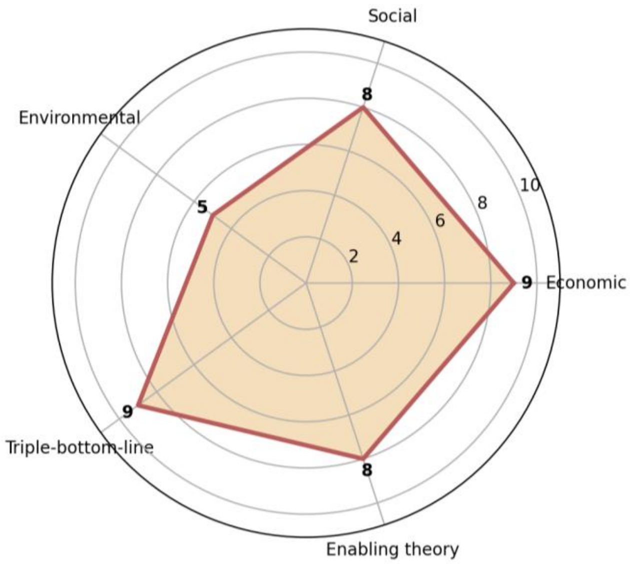

Figure 5. Evidence base by sustainability orientation

Table 2 shows frequencies are descriptive properties of the purposive theoretical sample. The result is that they are used to expose balance and gaps, not to estimate publication trends in the full research field.

Table 2. Descriptive evidence-map summary

Review Area Examined	Categories Found in the Reviewed Studies	What This Finding Means
Primary research domain	Sustainability application (11), ecosystem theory (10), AI-enabled service (9), governance and risk (6), organizational capability (3)	The reviewed studies cover outcomes, mechanisms, and governance issues
Ecosystem level studied	Multilevel (14), micro (12), macro (10), meso (2), meta (1)	Most studies examine multiple actors or direct service interactions; partner and learning levels are less studied
Sustainability focus	Economic (9), triple-bottom-line (9), social (8), enabling theory (8), environmental (5)	The studies address different sustainability outcomes and supporting theories
Publication period	2015–2019 (15), 2020–2022 (14), 2023–2026 (6), 2010–2014 (2), 2009 or earlier (2)	The evidence combines earlier service theories with recent AI research

5. An AI-Enabled Service Ecosystem Framework for Sustainable Development

5.1 Framework overview

Accordingly, the AI-powered service ecosystem is viewed as highly structured. The micro level consists of the focal service proposition, users, users, information, models, interfaces, and outcomes. The meso level consists of the existing relationships between service providers, technical suppliers, vendors, fulfillment providers, civil society organizations, and government agencies that collaborate and jointly deliver the service. Its macro level is shaped by rules, regulations, infrastructure, labor markets, cultural expectations, environmental constraints, and sustainability goals (such as the UN Sustainable Development Goals). Finally, the meta level of the framework is not a group of actors but a reflexive force capable of responding to evidence from all levels by transforming goals, models, relationships, and institutions.

Four cycles of training are used at all levels. Collaboration defines the problem, who are the beneficiaries and who may be excluded or suffer negative consequences, what outcome measures should be available, and what role, if any, AI should play. Development and collaboration ensure that data, models, and expertise in specific areas, as well as physical and human resources, are combined into efficient applications. Accountability integration considers benefits, burdens and externalities in relation to various stakeholders, thus measuring the activity against standard and sustainability criteria. Finally, learning cooperation requires adjustment in the intention and maintenance of decision processes. Each exercise cycle is repetitive; for example, integration may discover that the original problem was not fixed and that the project needs to return to the integration process.Figure 6 shows sustainable outcomes depend on recursive movement among co-design, co-development and delivery, co-evaluation, and co-learning. The result is that aI capacity crosses all levels, while co-creation and co-destruction remain simultaneous possibilities.

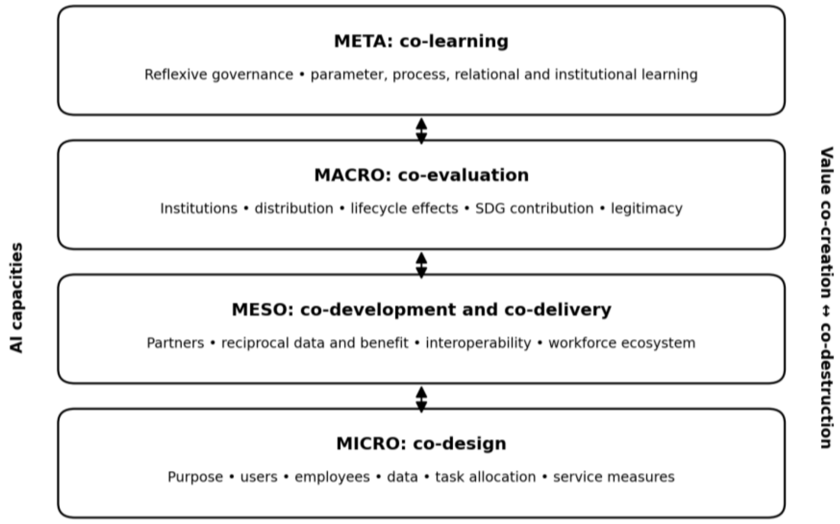

Figure 6. AI-enabled service ecosystem framework for sustainable development

Table 3 shows the framework prevents a direct inference from AI adoption to sustainable development. The result is that each level adds a distinct evidence requirement and governance responsibility.AI helps through intelligence, prediction, parenting and messaging capabilities. These four areas of support enable six key outcomes: goal alignment, aligned with environmental information, human-AI interaction, shared resource management arrangements, environmental regulation, and reflective learning. Each of these factors has a corresponding shadow. For example, goal conflict leads to proxy optimization; bad data leads to bias and brittleness; sudden perfectionism leads to deskilling or automation complacency; One aspect of resource management comes in the form of data output and output relationships; legal issues bring opposition and regulatory risks; and lack of learning memory leads to model shifting and environmental absorption.

Table 3. Multilevel framework and principal governance requirements

Ecosystem Level and Practice	Main Area Addressed at This Level	How AI Supports This Level	Sustainability Outcome Considered	Governance Actions Required
Micro: Co-design	Service problem, users, workers, data, and task allocation	Pattern detection, prediction, generation, and recommendations	Maintain service quality with economic, social, and environmental limits	Define purpose, include participants, record data sources, and keep human review
Meso: Co-development and Co-delivery	Partners, vendors, complementors, and workforce relationships	Coordinate organizations and support digital service delivery	Create shared value, circular incentives, and fair work conditions	Set data agreements, ensure compatibility, allow audits, portability, and exit
Macro: Co-evaluation	Institutions, communities, markets, and environmental boundaries	Support monitoring, allocation, and system-level decisions	Assess distribution, lifecycle effects, resilience, and legitimacy	Use impact assessment, appeals, remedies, and standards
Meta: Co-learning	Revision and improvement across all levels	Detect changes, combine feedback, and support future scenarios	Maintain positive outcomes during change	Use review cycles, independent checks, rollback options, and institutional learning

5.2 Micro level: co-designing an outcome-centered service

The micro level is driven by task difficulty, not model. By defining the desired outcome, the actors that achieve it, the baseline process, and why AI is appropriate, managers avoid a solution in which the derived model explains the problem. A credible concept of sustainability includes at least one budgetary outcome and clear economic, social and environmental constraints. For example, an AI scheduling service might seek to reduce waiting time while minimizing group differences, user overload, energy use, and error-related damage.

Co-design is necessary because much of the relevant knowledge is tacit and contextual. Frontline actors recognize differences, functions, and outcomes that are not visible through historical data. Users will see economic issues and benefits that manufacturers haven’t properly reported. Participation must be truly powerful: actors must be able to shape goals, evolutionary paths, competition options, and evaluation considerations. A meeting that cannot influence design is a piece of legislation without redistributing decision-making power.

Choosing an AI role is central. Low-risk, stable, and scalable tasks can be automated, outsourced, or distributed. Tasks with high uncertainty or critical importance need increased and necessary human intervention. If AI attempts intervention or sorts of issues by importance, it can be challenged as a tool. The restricted agent needs clear authority restrictions, controls, and reversals, and must have a shareholder designation. Such design integration is more common when these issues are addressed in the service plan, not in design technical documents.

Database design is also part of application design. The environment must indicate origin, legal status, use, exposure, extinction, frequency of modification, preservation, and possible reuse. Data reduction can be innovative: by reducing the amount of data processed, a service provider reduces privacy breach risks, infrastructure costs, and partner processing requirements. Data quality cannot be reduced to statistical criteria. It also depends on whether the groups truly reflect the goals of the current workplace, and whether the affected actors can identify and correct important mistakes. Micro-level indicators should assess efficiency with an eye towards sustainability. Other factors include, but are not limited to, accuracy for small groups, completion time, availability, ease of use, workload, breakdown rate, handling complaints, force working in one location, and avoidance of materials or travel. Cost reductions must be contrasted with cost increases; a time-saving service that allows customers to conduct free inspections can have a positive impact on one company's profits while undermining the value of another's equipment.

Proposition 1: The positive relationship between AI capability and sustainable service innovation is strengthened when co-design translates economic, social, and environmental goals into measurable service requirements.

Proposition 2: Human-AI complementarity improves sustainable service outcomes when task allocation reflects uncertainty, consequence, and contestability rather than technical feasibility alone.

5.3 Meso level: co-development, co-delivery, and reciprocal value

Services using AI are often based on a shared resource. Cloud providers provide accounting, vendors provide instances, organizations create domain information, service providers bring local expertise, and partners provide routing or complete resources. At the meso level, innovation depends on the quality of these relationships: a strong strategic model can fail if partners cannot integrate their operations, lack confidence in the use of data, or feel they are not getting enough value from their contribution.

Consistency should be the guiding principle: data sharing plans should not only specify availability and security, but also define purpose, value, accountability, updating responsibilities, and release conditions. Small partners may bring useful data but have limited bargaining power or analytical capacity; direct arrangements may involve shared ideas, capacity building, economic participation, consumption, or corporate governance. Without reciprocity, lifestyle can become a masquerade of withdrawal.

Collaboration has both technical dimensions (formats, interfaces, identifiers, semantic consistency) and institutional dimensions (approval, staffing, purchasing policies, liability, accountability levels). For example, a clinical AI service can effectively share information with partners but leaves clinicians uncertain about who should make a recommendation. If the technical integration outweighs the role description, the integration fails.

Digital applications offer many meso-level benefits for ensuring sustainability. Connected resources as well as potential analytics can support maintenance, rework, product remanufacturing, and performance-based contracting. Sjödin et al., 2023 suggests that a new rounded business model requires stronger capabilities than specialist AI; the employment contract should reward longevity, productivity, and productivity. Otherwise, efficiency outcomes may remain divorced from target specifications.

The meso level should include shared decision-making teams, shared assessments and case studies, paradigm change notification, and collaborative learning mechanisms. Vendor management is a key component: instance updates can transform the use of an application, without any visible changes to the environment. Contracts must assess that process data forward, transport, and publish. Risk may arise from sustainability if a significant amount of infrastructure or model development has occurred within a few partners.

Ultimately, the development of collaboration can reshape the lives of workers. AI has the potential to revolutionize the division of labor between employees, frontline and outsourced employees, and employees and customers. Transition management should consider not only capacity building and automation, but also the division of labor and the amount of work done by invisible users (e.g., database authoring, content classification, exception handling). In general, sustainability analysis should go beyond aggregate economics and focus on distributional effects.

Proposition 3: Reciprocal data and benefit governance mediate the relationship between cross-organizational resource integration and durable AI-enabled service innovation.

Proposition 4: AI-enabled efficiency contributes to circular and environmental outcomes when interorganizational incentives reward avoided throughput, asset longevity, and recovery rather than transaction volume alone.

5.4 Macro level: co-evaluating institutions, distribution, and externalities

The macro level considers whether the activity remains more profitable for the key stakeholders than for the direct stakeholders. Legal, legal, infrastructural, cultural, environmental and market factors frame such activities. Similarly, the deployment of AI tools transforms institutions by codifying new categories, evidence, types of controls, and new divisions of labor. Thus, innovative practices can have benefits and costs for the environment.

Accountability integration begins with articulating a theory of change that links activities to service outcomes, outcomes among users, and sustainable development outcomes. The causal chain must explain the logic that links the two. For example, a product that manages mobility can reduce congestion only if the recommendation process is feasible and not overcome by demand. A remote field service will increase accessibility if the screening process and language, technology, disability, and other barriers do not interfere with the target population. The distribution of incomes is at least as important as their average value. Uniform percentage increases in emissions may have disproportionately negative consequences for some populations. Similarly, findings should have practical validity: an organization should not disclaim its liability for an SDG indicator in the absence of an established contribution mechanism. Performance should be evaluated using shared data, access policies, user impact assessments, and environmental reviews. Wherever affected people can affect sustainable development, they must have access to information, rights, human considerations, and redress.

Environmental costs should be considered at the level of the total work, including the computing equipment. For example, the direct impact of the service takes the energy, water, equipment and other materials used to provide it. The indirect effect includes changes in waste, transportation, emissions, and other processes for emissions. In systemic terms, these consequences could be the effect of the tool on markets and behavior: better mobility could make using public transport less attractive, reducing emissions in one area while increasing them in another. Kaack and others. (2022) developed a three-dimensional assessment framework, which recognizes the importance of environmental factors. An optimal statistical model applied to a high-impact environment will have a larger environmental impact than a simple model that is analyzed in many related tasks. Thus, when comparing two tasks, the most relevant metric is their effects on the defined local boundary and time scale.

Legislative, regulatory, and regulatory frameworks can minimize barriers to new tools and ensure consistency in design and operation. By establishing clear records, assurances, data management, and accountability processes, the costs of uncertainty for partners and employees are reduced. Developers can provide opportunities for unsupervised experimentation of AI tools (sandboxes), with common features for testing, and public databases and standards settings. Thus, noncompliance should not be automatically conflated with desirability: communities may reject an activity even if it complies with the norms if they consider aspects such as surveillance or on-site reinforcement unacceptable.

At the macro level, the assessment should consider the scenarios and thresholds that indicate how the service will respond to disruptions and the conditions that warrant intervention. The former includes model failure, attacks on its infrastructure, the departure of a key supplier, fluctuations in product and output distribution, and changes in the display system or physics. By recognizing such capabilities, analysts can help ensure system resilience: when an AI service performs critical tasks, disruptions cannot exceed acceptable levels, and non-automated alternatives must be found.

Proposition 5: The contribution of AI-enabled service innovation to sustainable development is stronger when evaluation includes distributional, lifecycle, and rebound effects in addition to direct efficiency.

Proposition 6: Institutional legitimacy mediates ecosystem adoption and persistence when affected actors possess meaningful transparency, contestability, and remedy.

5.5 Meta level: co-learning and reflexive orchestration

The meta level is about using system-wide evidence to drive improvement. It is about reflective skills rather than performance. The orchestra can be asked to simplify the process, but no agent fully understands the situation and cannot impose its will on the system. Thus, cooperative learning processes require strategies that enable practitioners, practitioners, partners, auditors, regulators and communities to actively participate in the system and drive adaptation into action.

While model performance indicators (accuracy, precision, recall, replication, error rate, delay, safety violation) are important, they must be related to other operational, social, and environmental variables such as side effects, conflict effects, complaints, crashes, and environmental impacts. System-driven work may work within statistical expectations but has negative social consequences. New policies, market conditions, employee data, or employee behavior can make previous assumptions unrealistic.

Configuration can take different forms depending on changes in parameters, processes, relationships, or social configurations. Parameter learning refers to changes in thresholds, triggers, or model parameters. Process learning refers to alternative process design, collaboration, or analysis processes. Partnership learning refers to variations in business plans, partner responsibilities, or benefit sharing. Service learning requires adaptation to definitions, goals, or legal frameworks. Most learning processes in organizations are based on parametric learning while deep innovations are often disruptive and require strategic planning. Effective learning therefore requires building system advantages at all levels of enterprise architecture. This, in turn, leads to questioning of the original problem formulation and content, and to a willingness to use the tool when evidence emerges that it does not contribute to the intended goals.

The first step of the revision process can be configured to perform meta-level updates. Performance can be measured weekly by employees, with quarterly evaluations by a task force, and annual reviews by external partners. Important circumstances may cause assessments to be made at interim intervals. A lot of planning decisions can be maintained showing the reasons, decision, prosecutor and follow-up actions. AI can help with this process by not identifying anomalies, merging insights, projecting events, or recognizing patterns but relying on a single pattern for statistics that undermines the learning process. Systematic human trials, independent evaluations, and quality evidence are essential to challenge ideas and benefit the community. The process cannot rely on all concerns in a single metric but must strive to capture a broad range of perspectives and impacts.

Meta-level orchestration also includes sustainability-related trade-offs between different activities. Improving energy efficiency could affect the ability to address gateway issues, access more users, which could increase demand for infrastructure, and enhance privacy, which could reduce personal use. They are administrative issues rather than technical problems. A standardized planning process recognizes the importance of these trade-offs, engages affected parties, records evidence and opinions, and facilitates decision-making and review at a later date.

Proposition 7: Reflexive co-learning strengthens the persistence of sustainable outcomes by converting technical, service, social, and environmental feedback into changes at parameter, process, relational, and institutional levels.

Proposition 8: Ecosystem resilience increases when AI services retain human fallback, portability, rollback, and alternative delivery channels proportionate to service criticality.

6. Discussion

6.1 Theoretical contributions

This framework contributes to work-life research by showing how artificial intelligence transforms resource coordination. Digital technologies usually transmit or store information; cognition also involves consideration, mobilization, creation of roles and actions. The interpretation of artificial intelligence as infrastructure neglects its agency impact; however, interpreting her as an independent agent obscures human responsibility. The four-role typology reconciles these concepts by explaining the process of enterprise in limited governance arrangements.

Second, the paper links innovation to sustainable development through mechanisms and not through imaginary values. Artificial intelligence by itself is not a driver of sustainability. Its capacity to undertake new tasks emerges through specific collaborative practices, peer assessment, collaboration, contextual assessment, and reflective learning. These processes call into question the intention of efficiency to produce value, personalization to hide stereotypes, and automation of reflection to overwhelm. Thus, sustainability is an emergent tool and not an inherent characteristic of a model.

A third distinctive contribution is the integration of value creation and value destruction into the system. While operations research traditionally focuses on the pooling of collaborative resources, artificial intelligence highlights the potential of the same approach to deliver highly heterogeneous outcomes. Platform exchange, generosity, and collaboration can empower or enrich, liberate or empower, and democratize or homogenize. By systematically connecting each mode of possibility with a shadow, the framework assumes that ambiguity is conditional.

At the meta level, orchestration gets a new perspective as reflective learning. In the context of formal counselling, education sets up a new way of life; this framework explains the depth of learning by showing how sustainable adaptation can lead to contracts, changes in social resources, or even the use of intellectual property. Thus, continuous improvement can go beyond model fine-tuning.

6.2 Managerial implications

Administrators should prepare a job-scoring document for AI initiatives so that they specify the problem solved, beneficiaries, excluded users, role of AI, ownership, economic rights, environmental protection, environmental limitations, and performance indicators. It will standardize the co-design process and prevent outcome creep after launch.

Organizations should establish a lifecycle map to determine what major beneficiaries and stakeholders have to offer, profits, risks, and how they might respond to proposed changes before selecting vendors or data providers. It will identify areas of unequal integration and reveal instabilities in innovation. Contracts should cover model adjustment data, response support, statistical acquisition, data and model sampling, security assurance, and release conditions.

Functional-performance phases should distinguish between core functionalities and sustainability outcomes. Speed, accuracy, costs, and other similar indicators should address subpopulation performance, availability, user impact, energy or materials, complaints, and solutions. Several indicators should be explicitly tied to conclusions and decisions. Sustainability indicators that do not affect the continuity, restructuring, or resource allocation of the activity under review have no governance.

Finally, organizations should establish a challenging process in which various stakeholders can provide evidence on specific topics to inform evaluations of employee performance. Red teams, user calls, front-end reporting, independent assessments, and community feedback are all viable options. Administrative bodies should have a mandate to stop sampling, and resources should be allocated to investigating complaints. The importance of intellectual property protection should not be underestimated as frontline staff are often the first to identify concerns that dashboards do not adequately reflect.

Table 4 shows the diagnostic converts the conceptual framework into decision evidence. The result is that it is deliberately concise; sector-specific assurance and legal requirements must be added before deployment.

Table 4. Managerial diagnostic for AI-enabled sustainable service innovation

Assessment Question	Information Used for Assessment	Action/Decision Based on Assessment
Is the service problem and AI role clearly defined?	Outcome goals, baseline process, excluded uses, and authority limits	Continue only when AI provides clear contextual value
Do affected actors influence service design?	Documented changes from users and frontline workers	Redesign when participation cannot affect decisions
Are data relationships fair and transparent?	Data purpose, ownership, access rules, and benefit sharing	Modify arrangements if data exchange is one-sided
Are sustainability effects measured?	Economic, social, environmental indicators and risk measures	Continue only when benefits exceed identified harms
Can the service learn and adapt responsibly?	Reviews, feedback, audits, and improvement processes	Update or stop the system when risks increase
Assessment Question	Information Used for Assessment	Action/Decision Based on Assessment

6.3 Policy implications

Policy should promote coordination, rather than creating exclusive documents, to reduce transaction costs across the system. Frequent reporting procedures for sampling purposes, source of data, processing boundaries, environmental constraints, event history, and competitiveness are critical. Public procurement can drive external markets by clarifying requirements around life cycle assessment, availability of supply chains, labor migrations, consumption, and the declaration of a shared national interest.

At the same time, governments and development banks need to generate shared capacity, so that less connected players and regions have access to model training, better data, analytical tools, and communication support. The centralized concentration of resources, information and knowledge will exacerbate winner markets and geographic imbalances in AI applications, if public resources and cooperation are not deployed to counteract them.

7. Research Agenda and Testable Model

These eight statements can form the basis of an empirical study. Research enables the application of AI capabilities, effective collaboration, human-AI complementarity, interoperability, social regulation, learning memory, and sustainable innovative applications. The latter concept should be defined as a high-level construct, reflecting economic value and social and environmental sustainability (as opposed to measuring a single item). Structural equation modeling enables mediation to be analyzed by correlation and normativity and by differentiation by functional prediction or regulatory authority.

Table 5. Propositions and suggested empirical indicators

Research Proposition	Relationship Explained by the Proposition	Indicators Used to Measure the Relationship
P1	Better co-design alignment improves AI-enabled sustainable service innovation	Clear outcomes, stakeholder participation, and balanced performance measures
P2	Appropriate task allocation improves human–AI collaboration	Uncertainty handling, risk level, human override, and escalation processes
P3	Fair data and benefit sharing improves long-term AI service innovation	Data agreements, shared benefits, portability, and partner satisfaction
P4	Circular incentives improve environmental benefits from AI services	Resource savings, asset life extension, and recovery outcomes
P5	Broad evaluation improves sustainable development outcomes	Distribution effects, lifecycle impacts, and rebound effects
P6	Institutional legitimacy improves adoption and continuity	Transparency, contestability, and available remedies
P7	Reflexive learning improves ecosystem adaptation	Review frequency, learning mechanisms, and governance changes
P8	Responsible governance reduces value destruction risks	Risk controls, monitoring, accountability, and correction mechanisms

This table shows the indicators make the conceptual claims falsifiable. The result is that future studies should validate multi-item measures and avoid treating a single self-reported sustainability item as the dependent construct.

Long-term case studies will be equally useful in pursuing an AI tool from problem framing to deployment and institutionalization, capturing changes in actor roles and perspectives. Linked cases will examine similar but contractually or administratively different ecosystems, distinguishing why efficiency may be a stable outcome in one but return or withdrawal in another.

Network analysis could examine the interplay of resources and power: data transfer, provider aggregation, centrality, variable cost, and distribution of decision levels. These variables can be tested if highly centralized ecosystems innovate rapidly at first but prove less adaptable or illegitimate over time. Research should explore the conditions under which a neutral bystander or public policy is mutually beneficial.

Environmental research had to capture the net impact of all activities. Studies would need to report system boundaries, competing bases, processing rate, energy and fuel effects, shrinkage potential, and repeatability. Reporting on modeling-study intensity alone or contributions alone will not be sufficient: mixed methods can link ecosystem metrics to changes in user behavior and organizational motivation.

The variety of roles also calls for experiments that vary whether AI emerges as instrument, facilitator, mediator, or determinant, leaving the capacity intact. These outcomes may include trust ratings, trust, perceived control, willingness to compete, performance, and employee training. Greater autonomy can improve speed but reduce detection of errors when definitions or drift are weak.

Finally, meta-level collaborative learning requires process strategies. Future studies could dissect parametric, process, interaction, and context studies and test effects on resilience. Case studies can show whether organizations that document disputes, maintain fallback trails, and conduct peer-reviewed reviews recover faster and avoid breakdowns more often.

8. Limitations

The paper presents theoretical research, and the proposed model is not intended to be statistically significant. The 39 papers were identified using a purposive approach, and the aim was to obtain a comprehensive basis describing relevant concepts rather than an overwhelming array of sources. Pivot charts illustrate the content of these 39 themes, and coding was simplified by assigning a larger category to each domain. The next step in this research could be to conduct such a study with more coders and demonstrate their reliability, as well as to apply this framework to a larger dataset obtained from multiple sources.

This framework is designed for sectors; therefore, each field may require additional calibration or special adjustments. Specifically, the level of risk, user accountability, data rights, and automated consent in healthcare, finance, education, transportation, and public administration can vary and affect the implementation and outcomes of AI tools. The statements presented in this document are intentionally general, and specific circumstances may warrant further clarification and modification. Moreover, Rapid changes in the level of AI capabilities and standards, especially over a few years, may affect some practices, although the overall ecosystem will continue to be important.

9. Conclusion

AI can contribute to sustainable development by being integrated into services, created and managed as an enterprise. Technical integrity is necessary, but not sufficient to determine who benefits and who is responsible for costs or unintended consequences, or to ensure continuous improvement. Sustainable innovation requires collaboration at the micro level, collaborative development and collaboration at the meso level, distribution and lifecycle considerations at the macro, and collaborative reflection at the meta level.

This framework offers a transformation from a technological innovation approach based on a simple chain from adoption to innovation, to a normative and iterative account in which AI takes the form of a device, facilitator, mediator, and/or determinant. Each implementation scenario has implications for resource coordination and governance. Collaboration of economic, social, and social interests is possible, but so is discrimination, bias, favoritism, discrimination, disruptions to personnel and accountability, and other divisions. Consequently, leaders and policy analysts must establish mechanisms to transparently transparent transactions, promote voice and shared values, promote debate, and foster ideological change. Under these circumstances AI is not a prediction of sustainability, but the ability to retain to pursue it.

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