

AI Driven Multidomain Research: New Frontiers in Science, Business and Technology

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Abstract: Artificial intelligence (AI) is no longer confined to computer science. The same families of learning algorithms now predict protein structures, price financial assets, design semiconductor layouts and personalise customer journeys. This diffusion has created a new kind of scholarship in which methods, data and problem formulations move rapidly between science, business and technology. Yet the literature that documents this shift remains organised by discipline, and there is little integrative guidance on how AI-enabled knowledge actually travels across domains or on the institutional conditions under which such travel is productive. This paper addresses that gap through an integrative review and conceptual synthesis. We first consolidate representative evidence on how AI is reshaping inquiry in the natural sciences, in business and management, and in engineering and technology. We then propose the Multidomain AI Research Integration (MAIRI) framework, which explains cross-domain research value through three interacting layers: a foundation layer of shared data, compute and models; a translation layer comprising four transfer mechanisms (method, data and representation, problem-structure, and talent and tool transfer); and a governance layer that secures reproducibility, explainability, ethics and equitable access. Five propositions are derived to guide empirical testing, and a forward research agenda is set out. The paper contributes a common vocabulary for multidomain AI research and offers practical direction for universities, funding agencies and industry partners, particularly in emerging research systems such as India.

Keywords: artificial intelligence; multidomain research; interdisciplinary innovation; AI for science; business analytics; technology management; research governance; conceptual framework

I. INTRODUCTION

Artificial intelligence (AI) has moved from being a specialised subject within computer science to being an instrument of inquiry used across almost every field of scholarship. Deep learning (LeCun et al., 2015), transformer architectures (Vaswani et al., 2017) and large pre-trained foundation models (Bommasani et al., 2021) have produced a class of methods that learn useful representations from images, text, sequences, graphs and sensor streams with comparatively little task-specific engineering. Because these representations are not tied to any one discipline, the same techniques now predict protein structures (Jumper et al., 2021), explain cross-sectional stock returns (Gu et al., 2020), generate semiconductor floorplans (Mirhoseini et al., 2021) and personalise marketing interventions (Davenport et al., 2020). Economists of innovation describe this property by characterising AI as a general-purpose technology that is also a new method of invention: it raises productivity in existing tasks and, more importantly, changes how new knowledge is searched for and produced (Cockburn et al., 2018; Agrawal et al., 2018). The timing is significant. Several studies



report that research productivity has been falling, that the knowledge a researcher must absorb before reaching the frontier keeps growing, and that published work is becoming less disruptive over time (Bloom et al., 2020; Jones, 2009; Park et al., 2023). Teams, rather than individuals, now dominate knowledge production (Wuchty et al., 2007). Against this background, AI is frequently presented as a means of restoring momentum by compressing literature, widening hypothesis search and automating parts of experimentation (Wang et al., 2023).

What is less well understood is the *multidomain* character of this change. Most reviews are written from inside a discipline: AI for medicine (Topol, 2019), AI for Earth system science (Reichstein et al., 2019), AI for marketing (Davenport et al., 2020) or AI for supply chains (Toorajipour et al., 2021). Such reviews are valuable, but they say little about how a method validated in one field migrates to another, which institutional arrangements make that migration easier, or what new risks appear when techniques are lifted out of the context in which they were validated. A multidisciplinary opinion article by Dwivedi et al. (2021) catalogues challenges and opportunities across sectors, but it does not offer an explanatory framework for cross-domain movement.

This paper responds to that gap. It asks three questions. First, how is AI currently reshaping research practice in science, in business and in technology? Second, through which mechanisms does AI-enabled knowledge travel between these domains? Third, what foundational and governance conditions determine whether such travel results in reliable and socially useful knowledge? To answer these questions we undertake an integrative review of influential literature and synthesise it into the Multidomain AI Research Integration (MAIRI) framework, accompanied by propositions and a research agenda.

The paper makes three contributions. It consolidates dispersed evidence from three broad domains in a single comparable structure. It identifies four transfer mechanisms that, taken together, explain how AI creates value between fields and not only within them. And it links these mechanisms to a governance layer, arguing that reproducibility, explainability and equitable access are preconditions for multidomain value and not afterthoughts. The remainder of the paper presents the conceptual background (Section 2), the method (Section 3), the domain-wise synthesis (Section 4), the MAIRI framework and propositions (Section 5), key challenges (Section 6), a research agenda (Section 7) and implications and conclusions (Sections 8 and 9).

II. CONCEPTUAL BACKGROUND

2.1 AI as a general-purpose method of invention

General-purpose technologies are pervasive, improve over time and spawn complementary innovations. AI satisfies all three conditions, but its distinctive feature is that it improves the process of discovery itself. Agrawal et al. (2018) frame AI as a sharp fall in the cost of prediction; wherever a research or managerial task can be decomposed into prediction and judgement, cheaper prediction changes the economics of the entire task. Cockburn et al. (2018) add that deep learning operates as a research tool with wide applicability, so that its returns are spread across many application sectors. These returns arrive slowly, because organisations must first invest in complementary intangible assets such as data, skills and redesigned processes; Brynjolfsson et al. (2021) describe the resulting pattern as a productivity J-curve.

2.2 From disciplinary to multidomain knowledge production

The idea that valuable knowledge is increasingly produced in the context of application, by heterogeneous teams and across institutional boundaries, is long established. Gibbons et al. (1994) termed this Mode 2 knowledge production, and Etzkowitz and Leydesdorff (2000) described the accompanying university–industry–government relations as a triple helix. The science-of-team-science literature shows that cross-disciplinary collaboration can produce high-impact outcomes but carries heavy coordination costs arising from differences in vocabulary, methods and reward systems (Stokols et al., 2008; Fortunato et al., 2018). Hey et al. (2009) argued that data-intensive discovery constitutes a fourth paradigm of science alongside theory, experiment and simulation. AI extends that paradigm by supplying a shared methodological language—representation learning, optimisation and probabilistic prediction—that is intelligible across otherwise distant fields.



2.3 Human–AI complementarity

A second strand of literature concerns the division of labour between humans and machines. Jarrahi (2018) argues that AI is strongest in analytical tasks while humans retain an advantage in dealing with uncertainty, equivocality and values. Raisch and Krakowski (2021) show that automation and augmentation are interdependent rather than alternative strategies, and Shrestha et al. (2019) describe hybrid decision structures in which algorithmic and human judgement are sequenced. For research, this implies that AI should be analysed as a collaborator embedded in a socio-technical system. Krenn et al. (2022) similarly distinguish AI as a computational microscope, as a source of inspiration and, more ambitiously, as an agent of understanding.

2.4 The gap

Taken together, these literatures explain why AI matters for innovation, why knowledge production is becoming collaborative, and how humans and algorithms complement each other. What they do not provide is an account of the specific channels through which AI-enabled knowledge moves between science, business and technology, nor of the shared infrastructure and governance that such movement requires. The framework developed in Section 5 is intended to fill this space.

III. METHODOLOGY

The study adopts an integrative review design combined with conceptual model building. Integrative reviews are appropriate when the aim is to synthesise literature from different traditions and generate new frameworks, as distinct from aggregating effect sizes (Torraco, 2005; Snyder, 2019). Following Jaakkola (2020), the paper is positioned as a theory-synthesis article that integrates previously unconnected bodies of work and derives propositions from them.

Literature was identified through searches of Scopus, Web of Science and Google Scholar using combinations of terms relating to AI (artificial intelligence, machine learning, deep learning, foundation models) and to domains (scientific discovery, management, finance, marketing, supply chain, engineering design, communications). Priority was given to peer-reviewed articles in high-impact outlets, highly cited reviews and authoritative reports, with backward and forward citation tracking used to locate seminal contributions. Works were retained when they (i) described a substantive use of AI in research or practice within one of the three domains, (ii) discussed movement of methods or data between domains, or (iii) addressed governance of AI-enabled research. The retained material was coded thematically by domain, research task, AI technique and reported limitation. The purpose was conceptual coverage and not statistical representativeness; accordingly no quantitative meta-analysis is reported and no new empirical data are claimed.

IV. AI ACROSS THREE DOMAINS: A SYNTHESIS

4.1 Science

In the natural and life sciences AI now contributes at every stage of the research cycle. At the stage of hypothesis generation, models trained on the scientific literature have been shown to capture latent knowledge that anticipates later discoveries in materials science (Tshitoyan et al., 2019). At the stage of prediction, AlphaFold achieved accuracy in protein structure prediction competitive with experiment for many targets (Jumper et al., 2021), deep learning identified a structurally novel antibiotic candidate (Stokes et al., 2020), and graph networks have greatly expanded the catalogue of candidate stable inorganic crystals (Merchant et al., 2023). At the stage of experimentation, the vision of a robot scientist that closes the loop between hypothesis and test (King et al., 2009) has been advanced by autonomous laboratories for materials synthesis (Szymanski et al., 2023) and by language-model agents capable of planning and executing chemical experiments (Boiko et al., 2023). Physics-informed learning integrates governing equations with data, producing surrogates that respect known laws (Karniadakis et al., 2021), and hybrid modelling is recommended in Earth system science for the same reason (Reichstein et al., 2019). In medicine, AI supports image interpretation, risk prediction and workflow, although clinical validation remains uneven (Topol, 2019; Rajkomar et al., 2019). Kitano



(2021) has gone further in proposing the development of AI systems capable of autonomous discovery at the highest level as a grand challenge.

4.2 Business

In business and management, AI is primarily a technology for decision making under uncertainty (Duan et al., 2019). Davenport and Ronanki (2018) group enterprise applications into process automation, cognitive insight and cognitive engagement. In finance, machine learning improves the measurement of risk premia (Gu et al., 2020) and the assessment of consumer credit risk (Khandani et al., 2010). In marketing, AI enables personalisation and changes both firm strategy and customer behaviour (Davenport et al., 2020), while in services it progressively takes over mechanical, analytical and eventually intuitive tasks (Huang & Rust, 2018). In operations and supply chains, the dominant uses are demand forecasting, inventory optimisation and risk sensing (Toorajipour et al., 2021). At the level of the firm, Iansiti and Lakhani (2020) argue that AI-centred operating models remove traditional constraints on scale, scope and learning, and Mikalef and Gupta (2021) show that an organisational AI capability, comprising tangible, human and intangible resources, is associated with creativity and performance. Management research itself is changing: text mining, computer vision and large language models are increasingly used as research instruments to code qualitative material and measure constructs at scale.

4.3 Technology

In engineering and technology, AI is both a product and a design tool. Reinforcement learning has been used to produce chip floorplans comparable to those of human experts in far less time (Mirhoseini et al., 2021). In communications, end-to-end learning of the physical layer reframes transmitter and receiver design as a joint optimisation problem (O'Shea & Hoydis, 2017). In software engineering, language models trained on code generate functionally correct programs from natural-language descriptions for a meaningful share of benchmark tasks (Chen et al., 2021), altering how software for research and business is written. AI is also applied to climate-relevant engineering problems in energy, transport and buildings (Rolnick et al., 2022). These developments rest on rapid growth in computational demand, which raises environmental and access concerns discussed in Section 6 (Strubell et al., 2019).

4.4 Comparative summary

Table 1 summarises the synthesis. Two observations follow. First, a limited number of technique families recur in all three domains. Second, each domain contributes something distinctive to the others: science contributes standards of validation and mechanistic constraint, business contributes problem formulations centred on decisions and value, and technology contributes scalable infrastructure and design automation. These complementarities motivate the framework that follows.

Table 1. Representative uses of AI across science, business and technology

Domain	Principal research and decision tasks	Dominant AI technique families	Representative sources
Science	Literature-based hypothesis generation; structure and property prediction; simulation surrogates; closed-loop experimentation; clinical prediction	Deep representation learning; graph neural networks; physics-informed learning; generative models; language-model agents	Jumper et al. (2021); Stokes et al. (2020); Merchant et al. (2023); Szymanski et al. (2023); Boiko et al. (2023); Karniadakis et al. (2021); Topol (2019)



Domain	Principal research and decision tasks	Dominant AI technique families	Representative sources
Business	Forecasting; credit and risk assessment; personalisation; service automation; supply-chain sensing; strategy and operating-model design	Supervised learning on tabular and text data; recommender systems; natural language processing; optimisation	Gu et al. (2020); Khandani et al. (2010); Davenport et al. (2020); Huang & Rust (2018); Toorajipour et al. (2021); Mikalef & Gupta (2021)
Technology	Hardware design automation; learned communication systems; code generation; energy and infrastructure optimisation	Reinforcement learning; end-to-end deep learning; large language models for code; hybrid optimisation	Mirhoseini et al. (2021); O'Shea & Hoydis (2017); Chen et al. (2021); Rolnick et al. (2022)

Source: Authors' synthesis of the cited literature.

V. THE MULTIDOMAIN AI RESEARCH INTEGRATION (MAIRI) FRAMEWORK

The MAIRI framework (Figure 1) explains multidomain research value as the outcome of three interacting layers positioned beneath the three application domains. The framework is deliberately parsimonious, following Whetten's (1989) criteria that a theoretical contribution should specify what factors matter, how they are related and why.

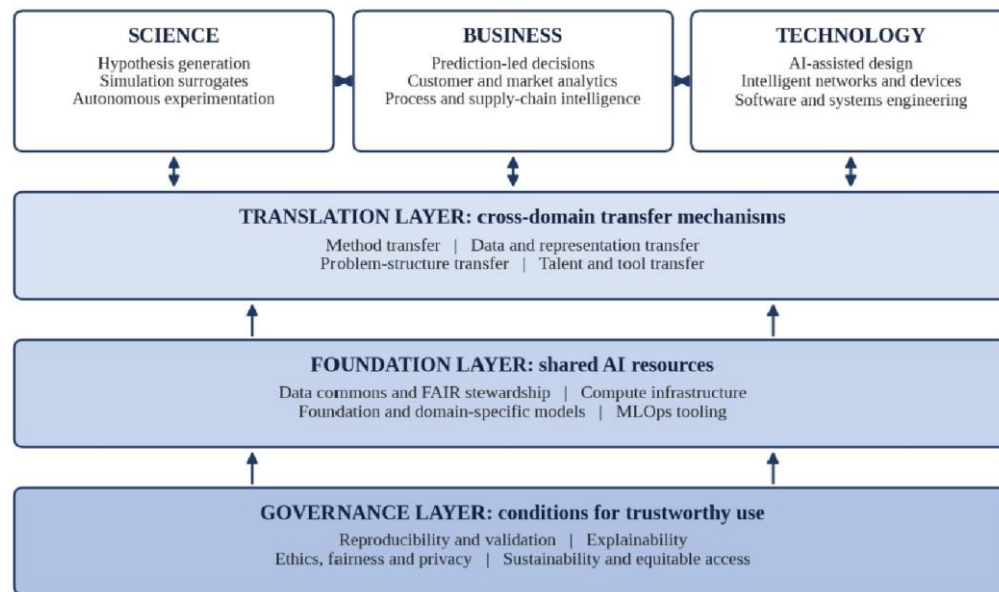


Figure 1. The Multidomain AI Research Integration (MAIRI) framework (authors' conceptualisation)

5.1 Foundation layer

The foundation layer comprises the shared resources on which all domains draw: curated data, compute, models and the engineering practices that keep them usable. Data that are findable, accessible, interoperable and reusable (Wilkinson et al., 2016) reduce the cost of entry for researchers from other fields. Foundation models pre-trained on broad data can be adapted to many downstream tasks (Bommasani et al., 2021), which makes them natural carriers of cross-domain



capability, but also concentrates dependence on a small number of providers. The layer therefore includes institutional arrangements for shared access to compute and models, without which multidomain work becomes the privilege of a few well-resourced organisations (Ahmed et al., 2023).

5.2 Translation layer: four transfer mechanisms

The translation layer is the core of the framework. We identify four mechanisms, summarised in Table 2, through which AI-enabled knowledge moves between domains. *Method transfer* occurs when an algorithmic approach validated in one domain is applied to another, as when sequence models developed for language are applied to proteins or to financial time series. *Data and representation transfer* occurs when datasets, embeddings or pre-trained models created in one context become inputs elsewhere, for example when satellite imagery curated for Earth science informs agricultural credit or insurance. *Problem-structure transfer* occurs when researchers recognise that two problems share a formal structure; chip placement, logistics routing and molecular design can all be posed as sequential decision problems over large combinatorial spaces. *Talent and tool transfer* occurs through the mobility of people and the diffusion of open-source frameworks and coding assistants, which carry tacit knowledge that publications do not (Nonaka, 1994).

Table 2. Cross-domain transfer mechanisms in the translation layer

Mechanism	What moves	Illustrative pathway	Characteristic risk
Method transfer	Algorithms, architectures and training procedures	Transformer sequence models moving from language to biology and to financial series	Violation of assumptions valid in the source domain; inflated performance through data leakage
Data and representation transfer	Datasets, embeddings and pre-trained models	Remote-sensing data from Earth science reused in agricultural finance and insurance	Bias and measurement error inherited from the source; privacy and licensing conflicts
Problem-structure transfer	Formal problem formulations and evaluation protocols	Sequential decision formulation shared by chip placement, routing and molecular design	Superficial analogy that ignores domain constraints and stakeholder values
Talent and tool transfer	People, tacit know-how, open-source libraries and AI coding tools	Data scientists moving between laboratories, firms and start-ups; shared MLOps stacks	Concentration of talent in industry; erosion of domain depth in hybrid teams

Source: Authors' conceptualisation.

5.3 Governance layer

The governance layer sets the conditions under which transfer yields trustworthy knowledge. It includes reproducibility and validation practices, explainability, ethical safeguards and attention to sustainability and access. The layer is placed at the base of the framework because weaknesses here propagate upward: a leaked test set or a biased training corpus contaminates every downstream application, irrespective of domain (Kapoor & Narayanan, 2023).

5.4 Propositions

The framework yields five propositions intended for subsequent empirical examination.

P1. *The stronger an institution's foundation layer (shared data, compute and models), the higher the volume and quality of its multidomain AI research output.*



P2. *The four transfer mechanisms are complementary: research units that activate several mechanisms simultaneously generate more novel cross-domain outputs than those relying on method transfer alone.*

P3. *The benefits of method and data transfer are positively moderated by the depth of target-domain expertise within the team; in its absence, transfer raises the incidence of invalid or non-reproducible findings.*

P4. *Governance maturity (reproducibility protocols, explainability and ethical review) mediates the relationship between cross-domain transfer and stakeholder trust in research outputs.*

P5. *Returns to multidomain AI research follow a J-curve: early investment in complementary intangibles depresses measured research productivity before later gains materialise.*

P1 and P5 draw on the economics of general-purpose technologies (Brynjolfsson et al., 2021; Cockburn et al., 2018). P2 and P3 extend the team-science argument that diversity yields novelty only when integration costs are managed (Stokols et al., 2008). P4 reflects evidence that explanation and transparency are central to the acceptance of AI-supported outcomes (Barredo Arrieta et al., 2020; Rai, 2020).

VI. CHALLENGES IN MULTIDOMAIN AI RESEARCH

Reproducibility and validity. Concerns that AI research is difficult to reproduce were raised early (Hutson, 2018). Kapoor and Narayanan (2023) document that data leakage has affected machine-learning-based studies across many scientific fields and frequently leads to over-optimistic conclusions. The risk is greatest precisely where methods cross domains, because adopters may be unfamiliar with the pitfalls of the method while method experts are unfamiliar with the data-generating process.

Illusions of understanding. Messeri and Crockett (2024) warn that reliance on AI tools may create scientific monocultures in which certain questions and methods crowd out others, producing the feeling of understanding more while in fact understanding less. Large language models can also generate fluent but unfounded statements (Ji et al., 2023), which places a premium on verification (Birhane et al., 2023).

Opacity. Many high-performing models are difficult to interpret. Explainable AI offers post hoc and intrinsic techniques (Barredo Arrieta et al., 2020), yet explanation needs differ between a physicist seeking mechanism, a manager seeking justification and a regulator seeking accountability (Rai, 2020).

Ethics, fairness and privacy. Reviews of AI ethics guidelines reveal convergence around transparency, justice, non-maleficence, responsibility and privacy, but divergence on interpretation and implementation (Jobin et al., 2019; Floridi et al., 2018). Data reused outside their original setting may violate the expectations under which they were collected.

Concentration and sustainability. Industry now holds a dominant share of the compute, data and talent required for frontier AI (Ahmed et al., 2023), and training large models carries material energy costs (Strubell et al., 2019; Bender et al., 2021). Vinuesa et al. (2020) conclude that AI can act as an enabler for many Sustainable Development Goal targets while inhibiting others, underlining the need for deliberate governance.

VII. RESEARCH AGENDA

Table 3 translates the framework into a research agenda. The priorities are to measure the constructs of the framework, test the propositions using bibliometric, survey and case-based designs, and evaluate institutional interventions.

Table 3. Research agenda derived from the MAIRI framework

Theme	Indicative research questions	Suitable designs
Measuring transfer	How can the four transfer mechanisms be operationalised? Which is most strongly associated with novelty and impact?	Bibliometric and citation-network analysis; text mining of methods sections
Team composition	What mix of domain and AI expertise maximises valid cross-domain output? What role do boundary-spanning ‘translators’ play?	Multi-level surveys of research teams; comparative case studies



Theme	Indicative research questions	Suitable designs
Foundation access	Does shared compute and data infrastructure narrow the gap between well-resourced and other institutions?	Quasi-experimental evaluation of national and consortium facilities
Governance effects	Do reproducibility checklists, model cards and ethical review improve downstream reliability and trust?	Field experiments; longitudinal audit studies
Emerging economies	How do multidisciplinary mandates and national AI missions shape multidomain research capacity?	Policy analysis; panel studies of institutional output

Source: Authors' conceptualisation.

VIII. IMPLICATIONS

For universities and research institutions. The framework suggests investing first in the foundation layer—shared datasets, compute allocations and research software engineering support—and then in deliberately designed translation mechanisms such as joint appointments, cross-faculty doctoral supervision and problem-centred laboratories. Management and commerce faculties are well placed to act as integrators because decision-centred problem formulation is their native competence. In India, the multidisciplinary orientation of the National Education Policy 2020 (Ministry of Education, 2020) offers an enabling policy context for such arrangements.

For industry. Firms benefit from treating academic collaboration as a channel for problem-structure transfer and not simply as a source of talent. Sharing anonymised data and evaluation benchmarks can attract scientific attention to commercially relevant problems while improving the external validity of academic work.

For policy makers and funders. Funding criteria should reward reproducible, well-documented multidomain work, support shared infrastructure to counter concentration, and require proportionate ethical review when data and models are reused outside their original context, consistent with international guidance (UNESCO, 2021).

IX. CONCLUSION AND LIMITATIONS

AI is dissolving methodological boundaries between science, business and technology. This paper has synthesised representative literature from each domain and proposed the MAIRI framework, which locates multidomain research value in the interaction of a shared foundation, four transfer mechanisms and a governance layer. The central message is that cross-domain transfer is the distinctive source of value in AI-driven research, but that it is also the point of greatest epistemic risk, and therefore requires deep target-domain expertise and mature governance.

The study has limitations. It is conceptual and relies on a purposive, not exhaustive, selection of literature; the three-domain partition is a simplification; and the propositions remain untested. The field is also evolving quickly, so specific technical examples will date. Future work should operationalise the constructs, test the propositions across institutional settings and extend the framework to the arts, humanities and social sciences, where AI raises related but distinct questions.

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