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VIEWPOINT

Trans-AI/DS: transformative, transdisciplinary and translational artificial intelligence and data science

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Abstract

After the many ups and downs over the past 70 years of AI and 50 years of data science (DS), AI/DS have migrated into their new age. This new-generation AI/DS build on the consilience and universology of science, technology and engineering. In particular, it synergizes AI and data science, inspiring Trans-AI/DS (i.e., Trans-AI, Trans-DS and their hybridization) thinking, vision, paradigms, approaches and practices. Trans-AI/DS feature their *transformative* (or transformational), *transdisciplinary*, and *translational* AI/DS in terms of thinking, paradigms, methodologies, technologies, engineering, and practices. Here, we discuss these important paradigm shifts and directions. Trans-AI/DS encourage big and outside-the-box thinking beyond the classic AI, data-driven, model-based, statistical, shallow and deep learning hypotheses, methodologies and developments. They pursue foundational and original AI/DS thinking, theories and practices from the essence of intelligences and complexities inherent in humans, nature, society, and their creations.

Keywords Trans-AI · Trans-DS · Trans-AI/DS · Transformative AI · Transformative data science · Transdisciplinary AI · Transdisciplinary data science · Translational AI · Translational data science

1 Introduction

The 70 years of artificial intelligence (AI) [1,2] and 50 years of data science (DS) [3,4] have demonstrated the good, the bad, and the ugly of their many generational evolutions and developments. AI has evolved into the field of AI science and engineering (AISE) [5]. Data science has evolved into data science and engineering (DSE) [6–9]. AI and data science are increasingly integrative and transdisciplinary, co-evolve, and co-develop. In fact, AISE and DSE fuse and converge, where DSE plays the foundational role of driving the new-generation AI and AISE. Therefore, we use AI/DS to represent this trending synthesis and co-development between AI and data science and their collaborative and transdisciplinary joint field.

AISE and DSE are at their X-generation age. Here, X refers to ubiquitous, variational, and forward-looking [6]. The resultant X-AI and X-DS explore X-domains, X-intelligences, X-complexities, X-mechanisms, X-data, X-analytics, and X-applications, etc. [1,6]. These pose many difficult problems and hitherto nonexistent perspectives and orientations going beyond the knowledge, capability, and capacity of singular disciplines. They require significant transformation, transdisciplinarity, and translation of AI/DS thinking, research, and practice. *Transformative, transdisciplinary and translational AI/DS*, covering Trans-AI (or TransAI), Trans-DS (or TransDS), and Trans-AI/DS for the joint field, feature the this new AI/DS age. Trans-AI/DS aim for the prominent, disruptive and unprecedented thinking, paradigms, trends, and directions and their theoretical and practical revolutions and developments. These include understanding and being enlightened by the essence of intelligences and complexities inherent in humans, nature, society, and their creations.

Transformative, transdisciplinary and translational research has attracted significant and increasing interest in science and engineering. In scientific history, transdisciplinary and translational approaches have fostered new perspectives, areas, techniques, and results. Typical areas are sustainability research [10], translational public health and translational medicine [11,12], biomedical research [13], and transformative digitalization.

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Pursuing Trans-AI/DS research requires disruptive, outside-the-box, and 'beyond' thinking. Examples of beyond thinking for Trans-AI/DS include:

- beyond hypothesis,
- beyond data-driven,
- beyond model-driven,
- beyond statistical i.i.d. assumptions, and
- beyond the fitting approach.

Below, we briefly discuss the perspectives, aspects, and opportunities of transformative, transdisciplinary and translational AI/DS both over the historical AI and data science evolution and in this X-AI/DS age. The discussion is inspired by and surpasses the scope and capacity of existing thinking and practice in transformative research [13], transdisciplinary science [10,14], and translational research [11].

2 AI/DS transformation, transdisciplinarity, and translation

A significant characteristic of this new generation of AI and data science, in comparison with their decades of multi-generation developments, is their maturity as an independent field. AI/DS have formed their own bodies of knowledge and their consilience and universology with all other bodies of domains and disciplines. This has fundamentally and continuously reshaped AI and data science as both an independent and universal field. To this end, AI/DS transformation, transdisciplinarity, and translation drive original, important and leading-edge AI/DS thinking, areas, paradigms, theories, technologies, engineering, and practices, etc.

Below, we highlight several important aspects of developing transformative, transdisciplinary, and translational AI/DS.

AI/DS thinking The restrictive capacity and reality of today's AI/DS suffer from the limitations and constraints in existing AI/DS thinking. These are partially attributed to the constrained thinking progression over AI and data science evolutions. For example, deep learning represents the state-of-the-art and dominates almost all areas where data, analytics, learning, and data-driven decision making play prominent roles. However, the existing deep learning theories [15] suffer from various fundamental bottlenecks. They cannot fulfill the ultimate AI/DS visions and address many challenges facing higher AI/DS expectations, such as human-level intelligence and artificial general intelligence (AGI). The foundational principle of deep learning still follows the 'fitting' mechanism, although feature engineering has been significantly weakened by the end-to-end approach. In fact, fitting has been an essential design thinking across almost all learning paradigms. A fitting-based deep learning system makes a parameterizable network fit its input when no ground truth is available. Alternatively, it builds the matching between input and output where output represents ground truth. The end-to-end fitting enhances the 'blackbox' nature of deep models with less interpretability, raising concerns on biased, variant or unfair fitting and unexplainable results. These limit their foundational potential in implementing human-like to human-level AI. Implementing the ultimate AI goals of developing intelligence at the human, natural and social level requires significant 'beyond thinking,' and paradigmatic and methodological shifts. Perhaps, we must continue to endeavor to deeply understand the origin and nature of how human, natural and social intelligences form, work, and evolve. We also need to fix the fundamental losses caused by various assumptions, constraints, and shortcuts (e.g., tricks) taken over the AI and DS history and developments.

AI/DS paradigm Mitigating the assumptions, constraints, and shortcuts in the evolving AI/DS development enlightens the potential of various paradigm shifts. Typical opportunities include:

- AI architectural design beyond specific logic-, module- or mechanism-oriented design;
- autonomous AI (AutoAI) and data science (AutoDS) beyond automated machine learning (AutoML) [16];
- non-IID informatics beyond i.i.d. approaches [17];
- decentralized AI (DeAI) beyond centralized AI (CeAI) and distributed AI (DAI) [18]; and
- process-oriented AI/DS problem-solving beyond point-based problem-solving.

These are increasingly explored in AI/DS tasks and systems, including in deep learning systems. Such paradigmatic transformations seek to understand and simulate the underlying intrinsic intelligence mechanisms, which drive human, natural, and social intelligence.

AI/DS discipline On the one hand, AI and data science have each evolved to be a rather independent scientific field—AI and data science, technology, and engineering. They incentivize the development of academic courses from undergraduate to doctoral degrees. On the other hand, the role of AI/DS in all disciplines of science is similar to the role played by computer science, mathematics and statistics [7,19]. AI/DS play a universal and essential role in every discipline in both natural and social sciences. They foster pan-, cross-, inter- and trans-disciplinary transformations and developments. They also further nurture new singular, cross-disciplinary, inter-disciplinary and trans-disciplinary areas and fields, such as for smart health, medicine, finance, disaster, and society resilience.

AI/DS translation AI and data science hardware and software, off-the-shelf products and solutions, and pretrained tools are increasingly available for the general public. In recent decades, the open science movement [20] has further significantly accelerated the translation of AI/DS theories to AI/DS practices, such as OpenAI. Translational pipelines spread from AI/DS research and design to AI/DS devices, products, applications, and services. Typical translational AI/DS applications include driverless cars, unmanned aerial vehicles such as drones, smart phones, smart industrial Internet of Things, and intelligent defense and military equipment.

AI/DS practice AI and data science practice has been transformed from specific-focus domains to almost all domains. The well-established AI/DS application domains include defense, finance, and medicine. AI/DS translation, applications and services have been rapidly disseminated to almost all domains in human, physical, social, and cyber spaces. AI/DS best practices go beyond the 'adopt-and-apply' approach to 'adopt-transform-apply' for tailored, personalized, and best developments, deployment, and outcomes.

Figure 1 shows the landscape of Trans-AI/DS with transformative, transdisciplinary, and translational AI and data science. These three AI/DS research thinking patterns and perspectives are interrelated, influence and promote each other. They co-evolve over iterative processes from transformation to translation and between transdisciplinarity and translation.

3 Transformative AI/DS

Transformative AI/DS aim to radically deepen, widen and enhance our understanding, characterization and implementation of human, natural, virtual and social intelligence and complexities. They develop new paradigms, areas, concepts, and frontiers of AI/DS; introduce new perspectives; disclose previously unknown areas; create an original understanding; and transfer knowledge over area, domain, or phase. These objectives surpass the traditional AI/DS foci on technological transformation for general purpose technologies and transformative societal change [21].

AI/DS transformation differ from the routine AI/DS development and progression in theories, technologies, tools, and applications. They inspire and facilitate fundamental and significant changes, original and new perspectives and initiatives, and highly distinguished and divergent thinking, research, innovation, or practice. These transformations may take place in AI/DS philosophy, thinking, goals, disciplines, paradigms, methodologies, technologies, or practices.

AI/DS philosophical transformation pursues the transformation of the scientific philosophy. The philosophical transformations in AI/DS

- drive new AI/DS thinking, goal, methodology, design, and development;
- define basic concepts, such as AI mind, mental state, intelligence, consciousness, and machines;
- specify basic questions, such as 'can a machine have mind, mental states, and human-level intelligence'; and
- determine basic arguments and propositions, such as 'a machine can be as intelligent as a human.'

These inspire typical philosophical transformation debates, such as on:

- from weak AI to strong AI,
- from narrow AI to general AI,
- from general intelligence to super intelligence, and
- from special-purpose to all-round and all-purpose AI/DS.

These inspire paradigm shifts from purposeful AI to AGI, human-like AI, and human-level AI, etc.

AI/DS thinking transformation pursues the transformation of the thinking for

- characterizing, mimicking and integrating human brain, thinking, and cognition into AI/DS systems;
- developing AI/DS systems with scientific thinking, such as critical, creative, constrastive, and disruptive thinking;
- enhancing AI/DS systems fusing multi-disciplinary thinking, such as neurological thinking, evolutionary thinking, mathematical thinking, statistical thinking, computational thinking, and data-driven thinking; and
- developing thinking machines with cognitive, scientific and disciplinary thinking traits, 'mental states', and human intelligence such as motivation, intention, memory, attention, learning, inspiration, and reflection, etc.

AI/DS goal transformation pursues the transformation of

- short-to-long-term scientific goals of the AI/DS field, such as pursuing general human-like intelligence by simulating human mind and cognitive capabilities, working mechanisms, and processes in perception, reasoning, planning, learning, behaving, and decision-making;
- technological goals of AI/DS research subfields and approaches, such as from questioning/answering to immersive and personalized conversational AI/DS;
- non-technical goals of AI/DS engineering and applications, such as for achieving economic, social, or political benefits and impacts; and
- specific goals such as of particular approaches, tasks, projects, and applications, for example, understanding X-intelligences and X-complexities embedded in or surrounding an AI/DS system and its behaviors, data, and decisions [6].

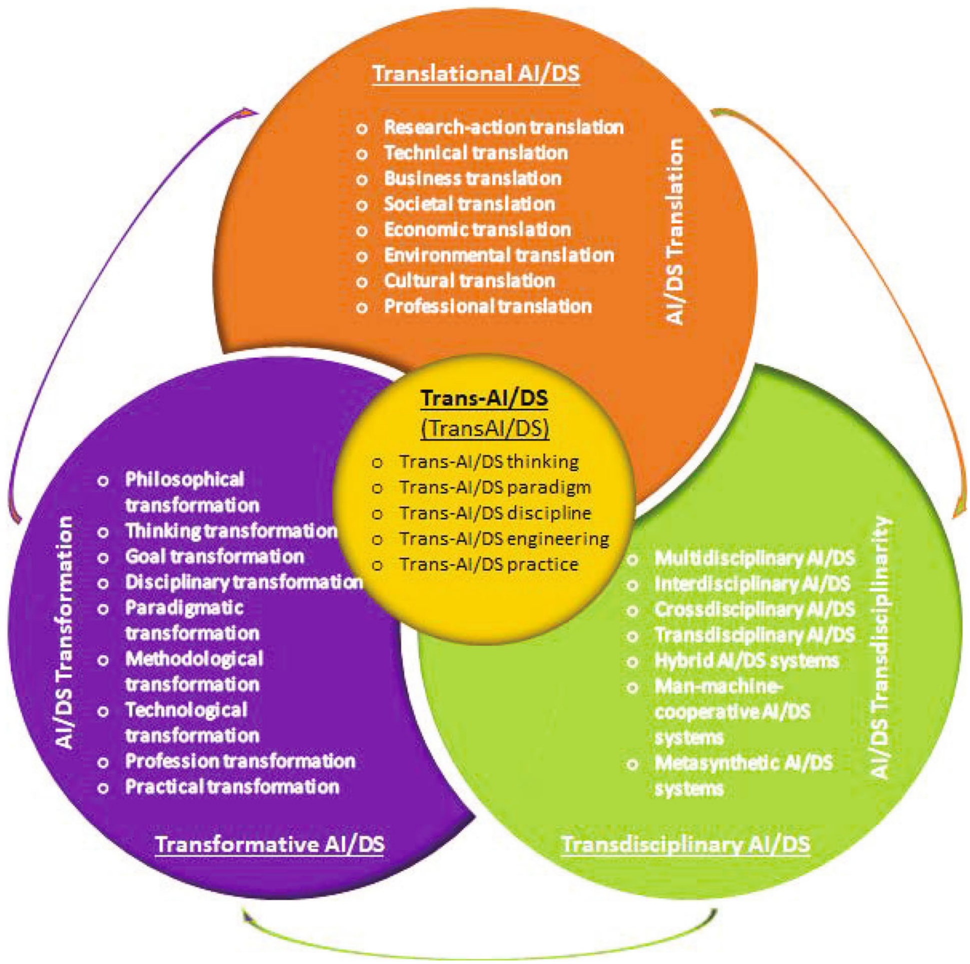

Fig. 1 Trans-AI/DS: transformative, transdisciplinary and translational artificial intelligence and data science

AI/DS disciplinary transformation pursues the transformation of the AI/DS field - AISE/DSE - and their bodies of knowledge. This may involve various areas of AISE and DSE, composed of

- *AI science* and *data science* with the areas and approaches forming AI/DS foundations, fundamentals, and technologies; and
- *AI engineering* and *data engineering* with the areas and approaches enabling AI/data engineering techniques, system engineering, management and governance [5].

Further, the AI/DS disciplinary transformation is embodied through

- *research area transformation* which makes AI/DS broader, deeper, and more general, open, unconstrained, and integrative; and
- *research topic transformation* which upgrades, expands and deepens the topics of interest in AISE and DSE, for example, toward unknown challenges, reality-based design, and ecosystem operations.

AI/DS paradigmatic transformation pursues the transformation of the paradigms in AISE and DSE. Over AI/DS history, *intelligence paradigms* have shifted from

- old intelligence paradigms: including object intelligence, symbolic intelligence, evolutionary intelligence, and connectionist intelligence

to

- modern intelligence paradigms: such as learning intelligence, behavioral intelligence, natural intelligence, networking intelligence, data intelligence, social intelligence, algorithmic intelligence, emotion intelligence, and system intelligence, etc. [6,22].

The paradigmatic transformation has migrated AI/DS

- theory: e.g., from symbolic to data-driven,
- design: e.g., from rule-based to scenario-oriented,
- programming: e.g., from mathematical programming to parameterized fitting,

- computing: e.g., transforming computing operations, architectures and environment, and
- engineering: e.g., AI methodology, processes, and benchmarking

from one generation to another over the AI/DS evolution [1].

AI/DS methodological transformation pursues the transformation of the methodologies guiding AI/DS theories and practices. Over AI/DS history, many AI/DS methodologies have been developed, including symbolic, connectionist, behavioral, situated, computational, nature-inspired, data-driven, human–machine-cooperative, pragmatic, hybrid, and metasynthetic AI [1]. Various AI methodological transformations have taken place to escalate or enrich these methodologies, e.g.,

- from individualism to collectivism,
- from connectionism to interactionism,
- from behaviorism to cognitivism,
- from reductionism to holism and systematism, and
- from object intelligence to metasynthetic intelligence [22].

In addition, new methodologies are emerging over time. A representative one is hybrid methodologies, such as neuro-fuzzy methods, and Bayesian deep neural learning, which has resulted in many hybrid, compound, and integrative research topics and areas [1,6].

AI/DS technological transformation pursues the transformation of AI/DS technologies. The AISE and DSE fields consist of a wide body of knowledge, covering many technical areas. Examples are symbolic reasoning, probabilistic reasoning, expert systems, knowledge engineering, computer vision, pattern recognition, data mining and knowledge discovery, machine learning, natural language processing, robotics, multiagent systems, evolutionary computation, deep neural learning, general deep learning, reinforcement learning, transfer learning, and federated learning. Approaches and techniques in these areas have been evolving over time, with significant new approaches, mechanisms, designs, and methods proposed. For example, federated learning has emerged as a combination of distributed learning, edge computing, and network communication [23]. Metaverse integrates mixed reality, human–machine interaction, game theory, and Web 3 [18]. And smart FinTech synergizes AI and data-driven discovery with financial domain knowledge and methods [24].

AI/DS profession transformation refers to the transformation of jobs and professions by AI/DS technologies and the emergence of new AI/DS-centric, -enabled or -created jobs and profession. AI/DS are profoundly shifting professions in almost all sectors, including Industry 4.0, smart manufacturing, intelligent officing, digital finance, and digital health and medicine. AI/DS also foster new professions and roles, such as digital artists, AI TV host, online chatbot and automated content generation such as those enabled by ChatGPT [25], and digital robot advisers.

AI/DS practical transformation promotes the transformation of AI/data engineering and practices. This may involve areas such as

- AI/DS design, e.g., of intelligent devices, chips, software, and architectures;
- programmable AI/DS, e.g., tools for AI programming, and building AI factories;
- AI/DS orchestration, e.g., of diverse AI/DS technologies and tools, and mixing AI/DS exploitation and exploration;
- AI/DS actionability, e.g., recommending best decision-making actions, providing explainable results, ensuring ethical codes and rules, and satisfying technical and business performance expectations;
- AI/DS benchmarking and testing, e.g., establishing technical, data, and performance benchmarks and evaluation measurement; and
- AI/DS governance, e.g., governing the healthy and quality development of AI/DS solutions and practices.

These practical transformations also involve the transformation to broader, deeper, higher, and faster objectives in implementing AI/data engineering and practices.

4 Multidisciplinary, interdisciplinary and transdisciplinary AI/DS research

Transdisciplinarity relates to but also differs from multidisciplinarity and interdisciplinarity in trivial-to-significant manners [10,14,26]. These research perspectives have been intensively involved in AI and data science.

- *Multidisciplinary AI/DS* research and perspective, where disciplinary approaches are independent or loosely coupled for specific tasking and problem-solving;
- *Interdisciplinary AI/DS* research and perspective, where disciplinary approaches interoperate and interact with each other for blended, cooperative or joint tasking and problem-solving; and
- *Transdisciplinary AI/DS* research and perspective, where disciplinary approaches transform each other and integrate for systematic, integrative to new tasking and problem-solving.

Figure 2 illustrates the formation of multidisciplinary, interdisciplinary and transdisciplinary AI/DS. These involve the mechanisms of multidisciplinarity, interdisciplinarity, and transdisciplinarity both within the AI/DS field and between AI/DS and other fields. In reality, multidisciplinary, crossdisciplinary, interdisciplinary, and transdisciplinary AI/DS are often interrelated, mixed or combined [27] to address complex problems.

Multidisciplinary AI/DS involves the thinking and approaches in multiple subfields for independent or collaborative tasking and problem-solving. One scenario of multidisciplinary AI/DS research is that the disciplinary approaches are independent of each other and play their own part in the global system and solution, respectively. In other cases, multidisciplinary approaches coordinate and communicate in forming a collaborative system and solution.

For example, in sequential AI/DS tasks such as medical diagnosis and modularized systems such as drones with modularity and composability, different techniques are applied at different phases or for different tasks, respectively. Each functional module operates as it is with self-defined coordination or communication with other parties in the overall tasking, collaboration, and problem-solving.

Interdisciplinary AI/DS connects and interoperates the thinking and approaches in multiple AI/DS subfields for hybrid, collaborative, or integrative tasking and problem-solving. Multidisciplinary approaches are connected, hybridized, blended, or interoperate with each other to form a higher level, hybrid, collaborative or integrative system. Common shareable standards, frameworks, and mechanisms may be implemented for the connectivity, interoperability, cooperation, coordination, and communication between disciplinary modules.

Many *hybrid AI/DS systems* involve interdisciplinary research and methods. A typical intelligent device and application is unmanned aerial vehicles with modularity, composability, and interoperability. Missions such as sensing, monitoring, search, data collection, data analysis, object detection, and attack are modularized, composable, and interoperable for unmanned aerial vehicles. These mission-specific AI/DS modules are connected and communicate with each other by integration techniques such as plug-and-play. A mission-oriented drone can then be composed and configured with various functional modules per its mission objectives and requirements. Each functional module operates independently with its own design and functionality. It also communicates with its incoming and outgoing modules for sequential tasking in the integrative intelligent system.

Transdisciplinary AI/DS transcend and integrate individualistic AI/DS research and applications in core and complementary fields or across independent disciplines. Similar to interdisciplinary research, transdisciplinary AI/DS also pursue collaborative, interoperable, and integrative research across multiple disciplines. However, transdisciplinary AI/DS transgress and transform the capabilities and capacities of constituent AI/DS areas and techniques. They bridge the silos across disciplines and disciplinary boundaries, and create new paradigms, concepts, frameworks, theories, and practices. These result in new and unified concepts, systems, and bodies of knowledge beyond the combination of multidisciplinary approaches. Transdisciplinary AI/DS systems involve the systematic integration, deep interaction and fusion, and transformation and new conceptualization of constituent disciplinary thinking and approaches.

Transdisciplinary AI/DS research fosters new areas, concepts, knowledge bases, and systems. Many well-developed and emerging areas and technologies are the result of transdisciplinary AI/DS research. Rather mature transdisciplinary areas include expert systems which fuse knowledge engineering, search and databases. Another example is robotics, which integrates many disciplinary developments such as modeling, biological engineering, electronics, cybernetics, and computing. Automated or autonomous intelligent devices such as driverless cars and unmanned aerial vehicles are emerging transdisciplinary directions. Another trending direction is sociotechnical AI/DS developments. They pursue transparent, responsible, equitable, explainable, accountable, and contestable systems by synergizing AI/DS with sociology. These areas are still quite immature in terms of forming their independent and systematic body of knowledge.

One typical area of transdisciplinary AI/DS research is to develop man–machine-cooperative systems. One promising area is to integrate cognitive computing with AI/data systems, such as by fusing brain science and informatics with intelligent systems. Another area is human-in-the-loop interactive systems, where humans interact with systems and provide critical human decisions and feedback to the system, such as in ChatGPT.

When AI/DS tasks involve open complex giant systems and problems, metasynthetic AI/DS systems may become essential. Metasynthetic systems synergize relevant multi-aspect intelligences and involve a qualitative-to-quantitative, human–machine-cooperative decision-making process for complex problem-solving. For example, a national macroeconomic decision-support system may involve experts in economics, finance, social welfare, trade, commerce, statistics, and planning. They collaboratively discuss, simulate, estimate, and evaluate national macroeconomic policies and plans during the decision formation [22].

Often, there is a migration from multidisciplinary to interdisciplinary and then transdisciplinary AI/DS research over time and development. For example, to date, as an emerging area, the concept and development of ethical AI is multidisciplinary and interdisciplinary. It is hoped that a fundamental understanding and more intrinsic theories, approaches, and tools will be developed over time to form an independent and systematic field of ethical AI.

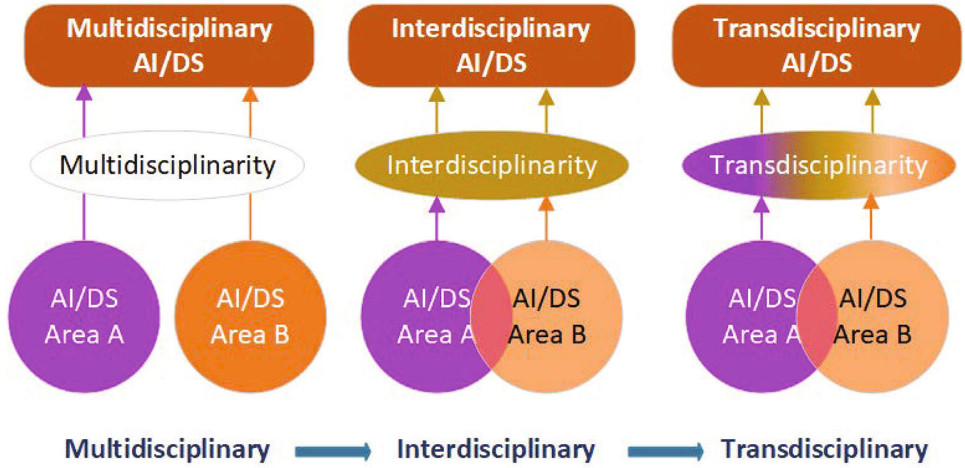

Fig. 2 Multidisciplinary, interdisciplinary and transdisciplinary AI and data science

5 Translational AI/DS

Translational AI/DS bridge the gaps between AI/data science and AI/data engineering. They convert AI/DS theories to practice. They aim to create methodologies, processes, and tools to enable the translational effect on technology, business, society, and economy. They also inform, enable or advise practical and actionable strategies or policies for best practice. In addition, they ensure the quality, performance, and impact of AI/DS engineering, products, solutions, applications, and practices.

AI/DS is increasingly translating technologies, business, society, and the economy into better features and futures. This is achieved by translating AI/DS theories and discoveries into technical advances, business transformation, societal developments, and economic growth. Translational AI/DS consist of technical translation, business translation, societal translation, and economic translation, etc.

AI/DS technical translation enables the translation into new integrative intelligent techniques, intelligent systems, and their technical benefits and impacts. Typical examples include smart FinTech, smart metaverse, medical imaging, intelligent epidemic management, smart disaster management, smart cities, smart home, and smart phones. In particular, intelligent devices, vehicles and systems such as drones and driverless cars represent a new age of manufacturing, featuring smart Industry 4.0.

AI/DS business translation enables the translation into business transformation, upscaling, new businesses, and efficiency lifting in public and private sectors. It can contribute to new, more and broader business benefits and impacts. For example, one can use AI/DS to support new forms of businesses, such as smart e-commerce with immersive metaverse support for immersive commerce. Smart marketplace retail systems like Amazon Go and Fresh are enabled by intelligent systems and algorithms. Digital health is empowered with smart medical diagnosis tools, medical and health analytics support. AI/DS is enabling workforce upskilling and capability uplifting and creating smart workplaces such as personalized work assistants, activity management, and scheduling.

AI/DS societal translation enables the translation into societal developments and services, sociotechnical systems. A typical area is to develop AI/DS for social impact or social good for people, organizations, community, and society. Social media, social networks, and AI/DS for social good are typical areas and applications of AI/DS societal translation. These are intelligent sociotechnical systems. They support the interactions and integration between humans and technology. AI/DS play an increasingly critical role in enabling personalized, active, proactive, and real-time technical support, tools, and services.

AI/DS economic translation supports the translation into the economy. They take the form of creating a new smart economy, AI economy, data economy, and smart finance, etc. These produce significant economic benefits and impacts. Examples are smart blockchain with risk, privacy and security protection, digital finance with intelligent robot advisors, and digital payment systems with contactless payment and mobile payment. There are also numerous applications in optimizing and intelligentizing supply-chain systems, logistics, trade, tourism, and education.

In addition, AI/DS have translated or are translating many domains and applications. Examples are AI/DS for translational environmental science and engineering, translational cultural and art research and applications, and translational professions, workplaces and working. AI/DS translation will continually overspread, deepen and advance the intelligentization, smartness, and wisdom of almost all domains and applications over time and space. In this regard, translational AI/DS will persistently reshape every aspect of our work, study, travel, living, and entertaining, etc.

Table 1 summarizes and illustrates various aspects of transformative, transdisciplinary and translational AI and

Table 1 Trans-AI/DS: Transformative, transdisciplinary and translational AI and data science

	Transformative AI/DS	Transdisciplinary AI/DS	Translational AI/DS
Thinking	Change, disruptive, divergent and beyond thinking	Cross-disciplinary, interdisciplinary and transdisciplinary thinking	Impact, effect and benefit-oriented thinking
Goal	New, original and significant developments beyond existing ones and filling gaps	New, systematic and integrative developments beyond individualistic capabilities and capacity	Converting theories to practices and AI/data science to engineering for effect, impact and benefit
Area	Transforming philosophy, thinking, goal, discipline, paradigm, methodology, technology, profession and practice	Multidisciplinary research, interdisciplinary research, transdisciplinary research	Technical, business, societal, economic, environmental and cultural translation
Approach	Transforming existing systems, transferring knowledge, radical change, and disruptive development	Transcending and integrating singular areas and techniques for new and unified developments, deep interaction and fusion, and systematic integration	Developing techniques, engineering, governance and management from AI/data science and research
Example	From narrow to general AI/DS, from purposeful to all-purpose development, from shallow to deep learning, from rule to scenario-based design	Hybrid, man–machine-cooperative, and metasynthetic AI/DS systems	AI/data engineering, products, solutions, applications, and practices such as drones, and driverless cars

data science. We interpret and compare these in terms of their research thinking, goals, areas, approaches, and examples.

6 Looking ahead

Trans-AI/DS encourage disruptive, original, critical, and creative AI/DS thinking and perspectives. They also foster new AI/DS research and development opportunities and also pose new challenges over the AI/DS evolution.

6.1 Trans-AI/DS thinking

Trans-AI/DS require thinking beyond existing AI/DS thinking. In the previous sections, we discussed many specific aspects regarding transformative, transdisciplinary, and translational AI/DS. Here, we further discuss several 'beyond thinking' [28] perspectives going beyond foundational and long-lasting AI/DS thinking. The 'beyond AI thinking' goes beyond existing scientific research perspectives, and specifically, beyond hypothesis-driven, data-driven, model-driven, domain-driven, and experience-driven research. Specifically, it goes beyond statistical i.i.d. assumptions and fitting.

Beyond existing scientific research Existing scientific research relies on some typical thinking patterns and methodologies. These include theoretical, model-driven, hypothesis-driven, problem-oriented, target-oriented, simulation-based, or data-driven research. These perspectives have been widely applied to almost all science fields, producing significant pools of knowledge. More creative, critical, transformational and disruptive scientific research requires new blue-sky research thinking, perspectives, and methodologies. New science and Trans-AI/DS require new scientific thinking and research, such as on system complexity-driven, nature and essence-driven, imagination-driven, curiosity-driven, counter-intuition, and unknown-driven research.

Beyond hypothesis Hypothesis-driven research has been generally applied as a starting point for further research across every scientific discipline, in particular a hypothesis test for statistical learning [29] and bioscience. However, the proposition, supposition, or proposed explanation may not be true and evidence-based. On the other hand, a predefined hypothesis may even misunderstand, mislead, or misinterpret the genuine essence of the underlying problem or system. For example, a Gaussian distribution is often assumed to characterize the informativeness of data. This, however, may not apply to many sources and problems of data, such as long-tail data. Beyond hypothesis thinking encourages hypothesis-free thinking, thinking initially with and then without a hypothesis, and transforming one hypothesis to another, etc.

Beyond model-driven Model-driven research has played a foundational role in software engineering, system design, and human–machine interaction [30]. Model-driven AI/DS involve a predefined model, which is tuned to match an underlying problem. A model often involves certain hypotheses and assumptions. Such hypotheses may not match the underlying problem domain, problem nature and complexities, resulting in over-qualified or under-qualified modeling. Beyond model-driven research thus suggests new perspectives. Examples include domain-driven [31] and model-free research, and semi-model-based research which partially involves the model and then further explores the genuine models fitting the problem well. Modeling problem characteristics and complexities is another example.

Beyond domain-driven Domain-driven research involves domain knowledge, factors, context, and expertise in design and development [32]. It complements model- and data-driven research for improving actionability such as in domain-driven actionable knowledge discovery [33]. It involves domain-driven designs and approaches but also goes beyond them. It may further involve human expertise, human-in-the-loop of the system, or human feedback and online interactions. Typically, such AI/DS systems have to involve broad domain factors and contexts, such as the underlying organization, society, stakeholder management, evaluation measurement, and deliverable requirements. Beyond domain-driven AI/DS will play a critical role in pursuing actionable intelligence.

Beyond experience-driven Experience-driven research has been widely applied in areas including business management [34], recommender systems, and reinforcement learning. It involves historical experience, data, feedback, and positive or negative online experiences in design and solution. Experience, history, and feedback may be false, biased, incomplete, unfair, or exceptional. It involves but does not depend on experience. It also verifies the nature, quality and relevance of the experience, aligns experience with the underlying problem well, and thinks beyond experience.

Beyond statistical i.i.d. assumptions One foundational statistical assumption is the i.i.d. assumption, which assumes samples in a dataset are independent and identically distributed (i.i.d.), or samples are i.i.d. drawn from a distribution. This statistical assumption has been taken as a default setting for almost all sciences, technologies and engineering.[1] However, this often contradicts real-life systems, behaviors, and data. The broad AI/data science body of knowledge has also been heavily dependent on this assumption. Many widely explored areas and techniques are based on the i.i.d. assumption. Examples are similarity and distance measures, Bayesian learning, reinforcement learning, and deep learning. Non-IID thinking [17] requires substantial rethinking of reality and non-IIDness. The non-IIDness may be composed of complex heterogeneities and interactions within and between systems, subsystems, objects, and object properties [17,35].

Beyond data-driven Data-driven research is regarded as the fourth scientific paradigm, which demonstrates significant advantages and potential for evidence-based AI/DS research. Data-driven discovery lets data tell the story about the underlying systems [6,36]. Data-driven research has to handle many fundamental challenges or concerns. Examples are data characteristics and complexities, quality of data, trustworthiness of data, misinformation in data, capability and capacity gaps in understanding data characteristics and complexities, and fairness and bias of data [37]. These challenge the commonly used 'end-to-end' approaches such as in deep learning and the data fitting approaches widely applied in mathematical modeling and machine learning. Data-driven approaches may incompletely, mistakenly, unfairly or biasedly characterize, treat or fit the above challenges. Beyond data-driven thinking thus suggests a data-free thinking, thinking with and without data, a deep understanding of data characteristics and complexities, and data quality-resilient research, etc.

Beyond fitting In general, both existing model-based and data-driven methods are essentially fitting oriented, i.e., matching input to output by tuning a model for a good fit. Accordingly, the goodness of fit[2] is regarded as an important statistical test and metric to evaluate the fitting performance. Though fitting has played a critical role in many classic research areas including curve fitting and machine learning [38], it is still essential for deep learning [15]. Both model-based and data-driven fitting may ignore the nature, quality and value of input and output, causing 'curse of fitting'. Such fitting approaches fail to achieve 'quality in and quality out,' or 'value in and value out.' Thus, beyond fitting thinking is essential. It is grounded on understanding the reality, complexity, quality, and value of input. It aims to develop corresponding models to explore the essence, complexities, quality and value of underlying problems, systems, and their data.

Beyond deep neural networks The existing fitting-based end-to-end deep learning systems transcend classic feature engineering-based machine learning with much higher capacity and flexibility. This is why deep learning works well when large data, high-volume parameterization, high-complexity models, and high-performance computing are available. Deep learning fitting transgresses classic fitting mechanisms and scale for much finer, lower-level microscopic and individualistic fitting. It develops and utilizes multi-grain, hierarchical, multi-aspect, and multi-method fitting. This often results in deeper input–output matching, more flexible scenarios, situation or setting-based fitting, and better learning performance. In contrast, deep models perform badly or ugly with limited data or without ground truth, such as the various failures in ChatGPT.[3] A fundamental is that such a multiple, microscopic, and all-round fitting nature does not resolve long-standing fitting problems. Deep models still suffers from underfitting or overfitting, causing high bias or high variance [39]. In addition, deep learning further incorporates fundamental bottlenecks and new significant challenges. These include

[1] https://datasciences.org/non-iid-learning/.

[2] https://en.wikipedia.org/wiki/Goodness_of_fit.

[3] https://github.com/giuven95/chatgpt-failures.

- 'curse of fitting' troubling unsupervised deep learning without fittable ground truths, and causing failures under drifting/shifting or open conditions [40];
- disentanglement and decoupling for disentangled and decoupled representation learning [41], which weakens or damages the intrinsic interactions and couplings in underlying systems and their data and behaviors;
- distributional vulnerability such as high-confidence predictions on test out-of-distribution samples [42], and
- architecture-, mechanism- and parameter-sensitive vulnerabilities, such as relating to the gradient-based back-propagation [43] and adversarial training [44].

6.2 Trans-AI/DS mechanisms

Trans-AI/DS thinking inspires new and hitherto nonexistent Trans-AI/DS disciplinary opportunities, concerted actions, and co-creative developments. These may cover various areas relating to the Trans-AI/DS paradigm, Trans-AI/DS research, Trans-AI/DS engineering, and Trans-AI/DS practice. In these aspects, Trans-AI/DS thinking is built into the problem definition, knowledge generation, and solution creation for Trans-AI/DS research, engineering, and practice.

Trans-AI/DS paradigms Trans-AI/DS rely on appropriate thinking, methodological, and engineering paradigms. Typical mechanisms and paradigms for transformative, transdisciplinary and translational research include curiosity, imagination, abstraction, catalysis, transcendence, transgression, transfer, hybridization, federation, reconfiguration, integration (synthesis), and metasynthesis [22,45].

Curiosity Discovery happens in curious human brains. Curiosity is the fuel for discovery, critical for inspiring early scientific thinking, and blue-sky breakthroughs. It fuels a passion for science [46]. An example of curiosity-driven discovery is the successful invention of airplanes, which countered the intuition "heavier-than-air flying machines are impossible." Curiosity-driven research explores known unknowns and focuses on the concept of "we do not know what we do not know" [6].

Imagination Imagination is another source of critical human intelligence and is the oil for scientific discovery. It fosters sensation, creativity and innovation through spontaneous, indirect, alternative, jumping, and changing thinking. It involves productive, reproductive or constructive identification. Research imagination [47] identifies novel ideas, spontaneous insights, alternate perspectives, possible futures, direct and indirect connections, and unconstrained, jumping and imaginary opportunities for AI/DS.

Abstraction Abstraction [48] plays a critical role in science. It conceptualizes, extracts, generalizes, simplifies, and compresses common, general, and high-level principles, concepts, rules, attributes, and knowledge from examples, and instances. Trans-AI/DS explore new abstraction thinking, methods, and tools through transformation, transdisciplinarity, and translation.

Catalysis Catalytic research is inspired by the catalysis in chemical reactions [49]. Trans-AI/DS support deliberative, reflective, counter-intuitive, or participatory thinking and approaches. They integrate thinking, knowledge, and methodologies outside the underlying domains, and disciplines. They also reorganize and restructure the underlying AI/DS constituents with new thinking, methodologies, knowledge, and materials.

Transcendence Transcendence goes beyond normalcy and constituents. Transcendent research bridges the boundaries between constituent disciplines, methodologies, and theories. Transcendent research for Trans-AI/DS creates new, coherent and unified perspectives, methodologies, and designs through surmounting and excelling the interactions and integration of AI/DS constituents.

Transgression Transgression violates the existent thinking, methodologies, theories, and methods for new, destructive and disruptive results. Transgressive research for Trans-AI/DS overcomes, surpasses, and scales up the capability and capacity of the underlying constituents. It approaches disruptive thinking, designs and tools through cross-boundary, and discriminative approaches such as reflexivity and intertextuality for AI/DS.

Transfer Transfer migrates merits gained from a known, explored, or grasped discipline or domain to another new, unknown, or open area. Transfer research for Trans-AI/DS explores known unknowns, from knowns to unknowns, and inspiration for 'we do not know what we do not know' in AI/DS research. A typical transfer research area is transfer learning [50], which moves knowledge learned in the source domain to a new, unexplored but connected target domain. Transfer research for Trans-AI/DS can also share, shift, and convey thinking, methodologies, and methods from one area to another in AI/DS.

Hybridization Hybridization enables the mixture or combination of two to multiple thinking traits, theories, methodologies and methods. It is a general approach for producing mixed, combined, joint, collaborative, or mutual developments. For Trans-AI/DS, hybrid approaches may be combined with other more destructive and constructive approaches in AI/DS to generate transformative, transdisciplinary and translational concepts, definitions, representations, systems, theories, or methodologies. To this end, it may combine methodologies and techniques from multiple disciplines [51].

Federation Federation associates local and global units to form distributed or federated architectures, networks, and systems in a centralized, decentralized or hybrid mode. Other similar approaches include alliance, coalition, union, conjunction, and consolidation. Federated research may support networked infrastructure, system coalition, and task allocation for distributed, cloud-based, and edge-based environments, such as in federated learning [52]. For Trans-AI/DS, such federated research may be further enhanced through transformation, transdisciplinarity, and translation.

Reconfiguration Transcending configuration, reconfiguration [53] supports new ways or a different form of combination or arrangement of constituent techniques, methods, or parts. Reconfiguration may involve different roles, capabilities, techniques, processes, or systems. New or different logic, hierarchy, structure, functionality, or processes may create new systems. Trans-AI/DS expect to incorporate transformative, transdisciplinary and translational thinking and operations into the rearrangement for AI/DS.

Integration Integration [54] supports the synthesis of multidisciplinary perspectives, multi-paradigms, multi-techniques, or multi-methods. It may synergize formal and empirical, theoretical and experimental, qualitative and quantitative, or subjective and objective research, thinking, knowledge, methodologies, and approaches. Trans-AI/DS expect the transformation, transdisciplinarity and translation of individualistic entities in AI/DS.

Metasynthesis Metasynthesis is a human-centered, and human–machine-cooperative methodology for iterative qualitative-to-quantitative problem-solving [22,45]. Metasynthesis synthesizes multiple types of intelligences with humans in the loop. Depending on system complexities, human intelligence, social intelligence, machine intelligence, data intelligence, and network intelligence may be of interest. Metasynthesis generally applies to open complex intelligent systems and problems [55]. Hence, their problem-solving requires the significant transformation, transdisciplinarity and translation of research paradigms, methodologies, techniques, knowledge, and intelligence.

Others Trans-AI/DS also involve other methodologies, theories, and techniques for transformative, transdisciplinary and translational developments. Examples include transforming mental activities such as attention, natural system mechanisms such as evolution, social mechanisms such as mentorship and supervision, and technical approaches such as contrast, competition (e.g., adversarial learning), and collaboration.

Trans-AI/DS research Trans-AI/DS research seeks paradigmatic shifts toward interdependent, interactive, interconnected, and integrative AI/DS research thinking, methodologies, and developments. Promising Trans-AI/DS research areas include natural-social, social-technical, societal -scientific, scientific-extra-scientific, and human–machine-cooperative research perspectives, orientations, and discourses. Trans-AI/DS research also supports inner-disciplinary, outer-disciplinary, and extra-disciplinary orientations, discourses, and developments. Trans-AI/DS engineering supports the interprofessional integration of knowledge, expertise, competencies, and experiences from collective and group members, and inclusive and exclusive developments.

Trans-AI/DS research approaches and orientations can be categorized into many perspectives, including:

- Thinking-oriented: building on human thinking traits such as curiosity, attention, and imagination;
- Methodology-oriented: building on scientific methodologies such as reductionism, holism, and systematism;
- Problem-oriented: building on recognizing, understanding and defining the underlying problem, and its characteristics and complexities;
- Goal-oriented: or mission-, target-, orientation- or task-oriented, focusing on goals, aims, and objectives;
- Setting-oriented: focusing on specific scenarios, situations, and tasks;
- Approach-oriented: focusing on developing, upgrading, and transforming a specific AI approach;
- Procedure-oriented: focusing on procedural forms, processes, organizations, structures, and workflows; and
- Solution-oriented: developing the solution space by unifying and transcending the relevant techniques and methods for the underlying problem.

6.3 Challenges

The concepts of transformation, transdisciplinarity, and translation have not formed consistent, and commonly agreed definitions, systems, and boundaries. Often, different highlights, specific orientations or discourses, or even conflicting arguments and proposals are available in the literature [10,26].

The Trans-AI/DS thinking and research raise various common challenges in pursuing the aforementioned Trans-AI/DS vision, objectives, and developments. Here, we list a few examples:

- Uncertainty recognition, modeling and management during transformation and translation;
- Disagreement and conflict resolution and paradoxical discourse between constituents during the pursuit of transdisciplinarity;
- Balance and tradeoff between conflicting and competing constituents and during transformation and translation;
- Unknownness [6,56], including unknown challenges, and opportunities for their identification and quantification during the transformation, transdisciplinarity, and translation.
- Complexity [57], including diversity, openness, hierarchy, interactions, and heterogeneities between constituents;

- Openness [22,45,58], such as open world, open problems, open set of classes [59], open interactions and relations, open boundaries, and open settings;
- Higher-level intelligence [16,60], such as curiosity, imagination, and attention-driven AI/DS research and development.

Specifically, AI and data science systems may be challenged by unknown problems, data, behaviors or environments. For example, unknown class labels, distributions, data quality issues, or contexts may appear ahead a deep learning task. In such cases, past experiences, common sense, exhaustive fitting may not help with their genuine understanding and problem-solving. Accordingly, Trans-AI/DS require unknown representation, reasoning, planning, learning, and analytics, which should represent, reason, plan, learn and analyze with unknownnesses.

Accordingly, Trans-AI/DS thinking and research require disruptive, original and foundational thinking, methodology, and development. They build on and go beyond the existing AI/DS and scientific thinking, paradigms, assumptions, approaches, and practices.

7 Concluding remarks

After the 70 years of AI and 50 years of data science, we are seeing their substantial renaissance in the age of big data, big models, big engineering, and big applications. The new-generation AI and data science require the transformation, transdisciplinarity, and translation of their existing generations of thinking, paradigms, theories, methodologies, designs, approaches, and practices. Trans-AI/DS thinking and research encourage and require thinking big, beyond thinking, outside-the-box thinking, and disruptive thinking. The new age of AI/DS is filled with ubiquitous, variational and forward-looking perspectives and opportunities. These will foster unlimited, nonexistent, and slow-to-rapid-changing orientations and discourses for transformative, transdisciplinary, and translational AI and data science.

In 2015, I initiated JDSA with Springer to promote the new era of data science and analytics [61], which was formally launched in 2016. Since then, JDSA has published 8 volumes in 4 issues every year, and the journal has been growing its reputation and leadership substantially in the era and field of data science. JDSA is ranked as a leading venue of data science with its highly diversified editorial board covering statistics, informatics, computing and other disciplines. JDSA sets up high expectation as to its paper quality, and low acceptance rate. In this new age, JDSA will further promote the significant transformation, transdisciplinarity, and translation of AI and data science.

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