ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

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www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940
www.ijasem.org
Vol 17, Issue 1, 2023

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

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Abstract

Data science (DS) and artificial intelligence (AI) have entered a new era after a tumultuous 70 and 50 years, respectively. The foundation of this next-gen AI/DS is the universalism and consilience of STEM fields. In particular, it encourages the development of Trans-AI/DS (i.e., Trans-AI, Trans-DS and their hybridisation) ideas, concepts, paradigms, methods, and practices by bringing together data science and artificial intelligence. The trans-AI/DS showcases the many ways of thinking, paradigms, techniques, technologies, engineering, and practices involved in transdisciplinary, transformational, and translational AI/DS. In this article, we will go over these significant orientations and paradigm changes. Beyond the traditional AI, data-driven, model-based, statistical, shallow, and deep learning theories, techniques, and advancements, Trans-AI/DS promotes large-scale and unconventional thinking. The core intelligences and complexity present in people, the environment, society, and their own inventions inform their pursuit of novel and unique ideas, theories, and methods in artificial intelligence and data science.

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 various generational evolutions and advancements of data science (DS) [3,4] and artificial intelligence (AI) [1,2] have shown the good, the terrible, and the ugly. AISE, or artificial intelligence science and engineering, is the current state of AI [5]. Data science and engineering, or DSE, is the next iteration of data science [6-9]. Data science and artificial intelligence are becoming more and more interdependent, cross-disciplinary, and collaborative. While AISE and DSE merge and converge, DSE is the engine that propels AISE and new-generation AI. Therefore, we refer to the emerging area of artificial intelligence and data science as AI/DS to reflect the tendency of synthesis and co-development between the two disciplines. The X-generation is when AISE and DSE were born. Ubiquitous, variational, and future-oriented are what X stands for here [6]. The X-AI and X-DS that emerge investigate X-domains, X-intelligences, X-complexities, X-mechanisms, X-data, and X- and X-applications, among other things [1,6]. These transcend beyond the scope, competence, and understanding of any one academic field and provide a plethora of new, challenging challenges and viewpoints. They call for a radical shift in perspective, a blending of disciplines, and the application of AI and DS principles in theory and practice. This new era of AI/DS is characterised by transformative, transdisciplinary, and translational approaches, including Trans-AI, Trans-DS, and Trans-AI/DS for the combined field. The goal of trans-AI/DS is to revolutionise and advance the most significant, groundbreaking, and distinctive ways of thinking, paradigms, trends, and directions in both theory and practice. Among them include gaining insight into and appreciating the complexity and substance of intelligence present in all things created by and for people, as well as in nature and society. There has been a marked and growing interest in scientific and technical pursuits of transformational, transdisciplinary, and translational research. New ideas, fields, methods, and findings have emerged throughout scientific history as a consequence of transdisciplinary and translational approaches. Common topics include studies on sustainability [10], biomedical research [13], disruptive digitalisation [14], and translational public health and medicine [11,12].

ISSN2454-9940
www.ijasem.org
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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], transdisci- plinary 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, nat- ural, 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, disas- ter, and society resilience.

AI/DS translation AI and data science hardware and soft- ware, off-the-shelf products and solutions, and pretrained

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN2454-9940
www.ijasem.org
Vol 17, Issue 1, 2023

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.

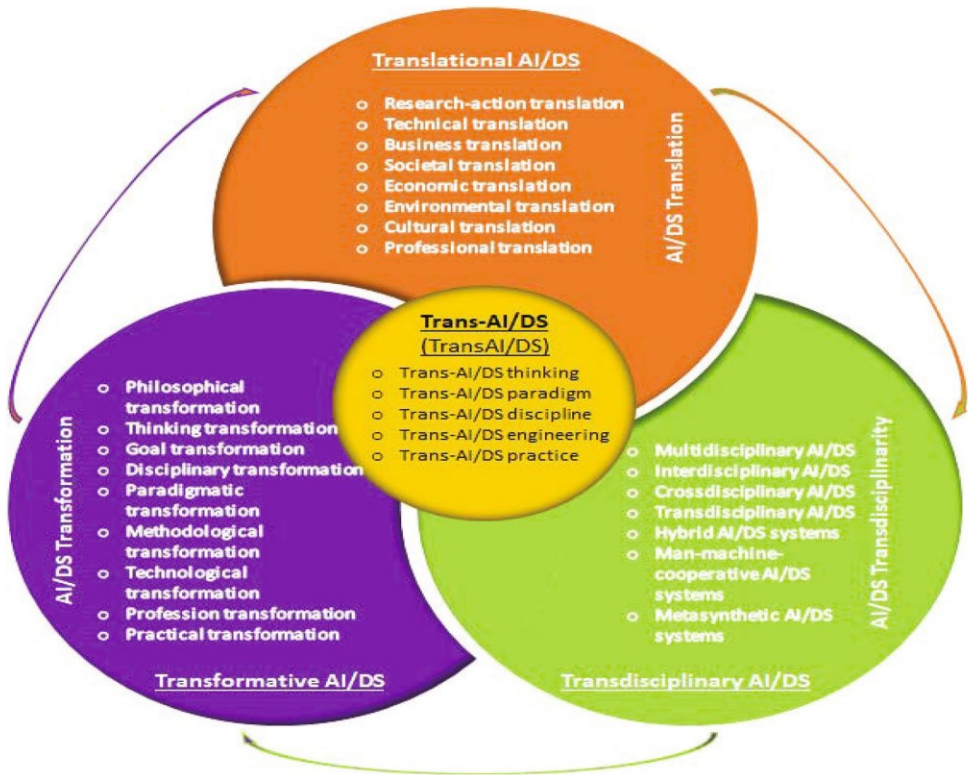
Transformative AI/DS

Human, natural, virtual, and social intelligence and complexity are the focus of transformative AI/DS, which seeks to dramatically expand, deepen, and improve our knowledge, characterisation, and implementation of these topics. fresh paradigms, domains, ideas, and frontiers of AI/DS are developed by them. They also provide fresh viewpoints, uncover places that were previously unknown, generate an original understanding, and transfer knowledge between domains, phases, and locations. These goals go beyond what artificial intelligence and data science have traditionally aimed to achieve, which have been general purpose technology transformation and transformative social change [21]. The normal growth and improvement of AI/DS theories, technologies, tools, and applications is distinct from AI/DS transformation. They motivate and enable ground-breaking shifts, fresh viewpoints and initiatives, and exceptional and unconventional approaches to study, practice, or research. Any number of areas within artificial intelligence and data science have the potential to undergo radical changes in the near future.

Philosophy of science is being pursued by AI/DS as it undergoes philosophical development. Advancements in AI/DS and their philosophical implications • Prompt fresh approaches to AI/DS research, theory, methodology, and development; • Outline fundamental ideas like AI mind, mental state, intelligence, consciousness, and machines; • Identify fundamental questions like "can a machine have mind, mental states, and human-level intelligence?" and "a machine can be as intelligent as a human." Common philosophical transformation disputes stem from these, including those about: • From inadequate AI to robust AI; • From specific AI to generic AI; • From GI to SU; and • From AI/DS designed for a single purpose to AI/DS designed to handle a wide variety of tasks.
Inspiring paradigm changes towards AGI, human-like AI, human-level AI, etc., they pique people's interest in artificial general intelligence (AI) beyond its current use for specific purposes.
Artificial intelligence and data science are actively working to revolutionise the way we think about • defining, imitating, and integrating human brain, thinking, and cognition into AI/DS systems; • building AI/DS systems with scientific thinking, including critical, creative, contradictory, and disruptive thinking; • improving AI/DS systems that combine multi-disciplinary thinking, including neurological, evolutionary, mathematical, statistical, computational, and data-driven thinking; and • creating thinking machines with cognitive, scientific, and disciplinary thinking traits,'mental states, Pursuing the transition of AI/DS goals
• 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, work- ing 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 immer- sive and personalised conversational AI/DS; • non-technical goals of AI/DS engineering and applica- tions, such as

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN2454-9940
www.ijasem.org
Vol 17, Issue 1, 2023

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,

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

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- 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.

3 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 cou- pled 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 inte- grate 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, as well as interdisciplinarity, both within and outside of the AI/DS domain. There is a lot of overlap, mixing, or combining of multi-, cross-, interdisciplinary, and transdisciplinary AI/DS approaches [27] when dealing with difficult challenges. An approach to artificial intelligence and data science that is multidisciplinary draws on ideas and methods from a wide range of disciplines to tackle problems either alone or in tandem. It is possible for several fields to work together in AI/DS research, with each field contributing to the overall system and finding its own unique answer. In other instances, a collaborative system and solution are formed via the coordination and communication of diverse techniques. various strategies are utilised at various stages or for distinct tasks in sequential AI/DS activities like medical diagnosis and modularised systems like drones with modularity and composability, respectively. Every working module does its own thing while communicating and coordinating with others to complete tasks and solve problems. When researchers in different areas of artificial intelligence and data science work together, they create interdisciplinary AI/DS. This allows for hybrid, collaborative, or integrative problem-solving. A higher level, hybrid, collaborative, or integrative system is formed when multidisciplinary techniques are linked, hybridised, blended, or interoperate with one other. Connectivity, interoperability, collaboration, coordination, and communication across disciplinary modules may be enhanced by implementing common shareable standards, frameworks, and methods. Interdisciplinary research and approaches are used by many hybrid AI/DS systems. Typical intelligent devices and applications include composable, modular, and interoperable unmanned aerial vehicles. Unmanned aerial vehicles are capable of tasks including sensing, monitoring, searching, data collecting, data processing, object identification, and assault, and they are designed to be modular, composable, and interoperable. Through integration methods like plug-and-play, these AI/DS modules tailored to individual missions are linked and able to interact with one another. Then, different mission-oriented drone modules may be assembled and set up according to the mission's needs and goals. The design and functionality of each functional module allow it to operate autonomously. The integrative intelligence system's incoming and outgoing modules are also able to interact with it, allowing for sequential tasking. Research and applications of AI/DS across core and adjacent subjects, as well as across separate disciplines, are brought together in transdisciplinary AI/DS projects. Collaborative, interoperable, and integrative research across various fields is the goal of transdisciplinary AI/DS, just as it is in multidisciplinary research. The capabilities and powers of the component AI/DS domains and approaches are transcended and transformed by transdisciplinary AI/DS. They produce new ideas, frameworks, theories, and practices; break down barriers across disciplines; and bridge existing silos. Beyond the integration of interdisciplinary methods, they lead to novel and cohesive frameworks, information, and ideas. Systematic integration, deep interaction and fusion, transformation, and novel conceptualisation of component discipline thinking and methods are all part of transdisciplinary AI/DS systems. New fields, ideas, databases, and systems are created via transdisciplinary AI/DS research. The fruit of transdisciplinary AI/DS research is a plethora of established and new fields and technologies. Expert systems are an example of a well-established cross-disciplinary field that combines knowledge engineering with search and databases. Robotics is another field that exemplifies this by bringing together recent advances in modelling, computer science, biology, electronics, cybernetics, and computing, among others. Emerging transdisciplinary directions include automated or autonomous intelligent gadgets like driverless autos and unmanned aerial aircraft. Progress in sociotechnical AI/DS is another area of interest. They combine AI/DS with sociology to create systems that are open, fair, explainable, accountable, and subject to challenge. When it comes to developing their own distinct and organised corpus of knowledge, many fields are still in their infancy. The development of man-machine cooperative systems is a common focus of transdisciplinary AI/DS research. The merging of fields like cognitive computing, brain science, and informatics with intelligent systems is one exciting prospect in the realm of artificial intelligence and data systems. Similarly, ChatGPT is an example of a person-in-the-loop interactive system, which allows for human decision-making and feedback to be integrated into the system. As AI/DS tasks increasingly include open, complicated, and massive systems and challenges, metasynthetic AI/DS systems may emerge as paramount. A metasynthetic system is one that uses a qualitative-to-quantitative, human-machine cooperative decision-making method to solve difficult problems by combining suitable multi- faceted intelligences. For instance, professionals in the fields of finance, economics, social welfare, commerce, statistics, and planning may be involved in a national macroeconomic decision-support system. When making decisions on national macroeconomic policies and programs, they work together to debate, model, estimate, and assess these things [22]. Research in artificial intelligence and data science often evolves from a multidisciplinary focus to an inter-disciplinary one, and eventually a transdisciplinary one. The idea and development of ethical AI, for instance, spans several disciplines and is still in its early stages as a developing field. As time goes on, we can only hope that a distinct and methodical area of ethical AI will emerge, based on a deeper comprehension of the topic and more inherent ideas, methods, and tools.

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN2454-9940
www.ijasem.org
Vol 17, Issue 1, 2023

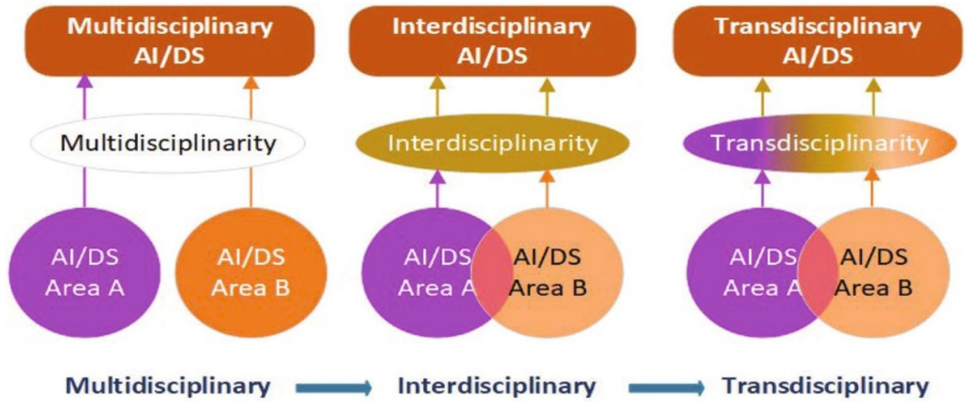

Fig. 2 Multidisciplinary, interdisciplinary and transdisciplinary AI and data science

4 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

ISSN2454-9940
www.ijasem.org
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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.

5 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 method- ologies. 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, transforma- tional 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.

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN2454-9940
www.ijasem.org
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Apart from domain-driven Knowledge of the domain, relevant aspects, context, and development and design experience are all essential components of domain-driven research [32]. For example, in domain-driven actionable knowledge discovery, it enhances actionability and complements data-and model-driven research [33]. It includes, and goes beyond, domain-driven strategies and designs. Expertise from humans, humans involved in the system's operation, human input and online interactions are all possibilities. The underlying organisation, society, stakeholder management, evaluation measurement, and deliverable needs are some of the broad domain aspects and settings that are usually involved in such AI/DS systems. The pursuit of actionable intelligence will rely heavily on AI/DS beyond domain-driven applications. Prior to relying on Areas such as reinforcement learning, recommender systems, and business management [34] have all made extensive use of experience-driven research. Design and solution include past experiences, facts, comments, and good or bad online encounters. Feedback, experiences, and histories could all be skewed, partial, unjust, or out of the ordinary. While prior knowledge is helpful, it is not necessary. In addition to checking the experience's veracity, quality, and applicability, it does a good job of relating the experience to the underlying problem and going beyond the experience itself. Looking beyond the assumptions of independent variables in statistics The i.i.d. assumption is a cornerstone of statistics; it states that all dataset samples are either randomly selected from a distribution or are independently and identically distributed. Almost every field of research, technology, and engineering uses this statistical assumption as its default setting.1 Nevertheless, this often runs counter to actual systems, behaviours, and facts. The extensive corpus of knowledge in artificial intelligence and data science has likewise relied substantially on this premise. The i.i.d. assumption is the foundation of several extensively researched fields and methods. Some examples include deep learning, reinforcement learning, Bayesian learning, and similarity and distance measurements. A radical reevaluation of reality and non-IIDness is necessary for non-IID thinking [17]. Systems, subsystems, objects, and object attributes may all contribute to the non-IIDness, as can complex heterogeneities and interactions [17,35]. Above and beyond data-led Evidence-based artificial intelligence and data science studies stand to benefit greatly from data-driven research, which is considered the fourth scientific paradigm. With data-driven discovery, the data may reveal the hidden workings of the systems [6,36]. Many basic issues or problems must be addressed via data-driven research. Some examples include data's qualities and complexity, its reliability and accuracy, any disinformation it may include, and any gaps in knowledge or skills related to data's attributes and swap out the data fitting methods used extensively in mathematical modelling and ML for more conventional "end-to-end" methodologies used in deep learning. When it comes to describing, treating, or fitting the aforementioned difficulties, data-driven techniques may be inadequate, incorrect, unjust, or biassed. Therefore, going beyond data-driven thinking implies doing research that is robust to data quality, thinking both with and without data, and having a thorough grasp of data features and complexity. Above and above what is required The majority of current approaches, whether they are data-driven or based on existing models, are fitting orientated, meaning they aim to optimise the relationship between input and output via model tweaking. Thus, a significant statistical test and measure for evaluating fitting success is the goodness of fit2. Deep learning relies on fitting, even if it has been crucial in several traditional fields of study, such as curve fitting and machine learning [38], [15]. 'Curse of fitting' may occur when either model-based or data-driven fitting fails to take into account the input and output's quality, value, and nature. You can't have "quality in and value out" or "quality in and quality out" using these fitting methods. Therefore, thinking outside the box is crucial. Recognising the input's realism, complexity, quality, and worth forms its foundation. The goal is to create models that can help us understand the data, systems, and issues at their core by delving into their intricacies, quality, and value. In addition to ANNs, With far more capacity and flexibility, the current fitting-based end-to-end deep learning systems outperform traditional feature engineering-based machine learning. Because of this, deep learning is most effective in scenarios where there is access to big data, lots of parameterisation, complicated models, and powerful computers. Deep learning fitting scales for much finer, lower-level micro-scopic and individualised fitting, bypassing standard fitting methods. It creates and employs multi-aspect, multi-method, hierarchical, and multi-grain fitting. Better learning performance, more adaptable scenarios, situation- or setting-based fitting, and deeper input-output matching are common outcomes. As seen by ChatGPT's many failures, deep models, on the other hand, perform poorly or horribly when faced with little data or an absence of ground truth. A basic is that this kind of repeated, tiny, all-around fitting won't fix issues with fitting that have persisted for a long time. Underfitting and overfitting are still problems with deep models, leading to substantial bias and variance, respectively [39]. Deep learning also contains new major obstacles and basic bottlenecks. Among them are questions of complexity, data bias, and equity [37]. Presented below are challenges.

- '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 backpropagation [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 pro- ducing 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, transdis- ciplinary and translational concepts, definitions, representa- tions, 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 alloca-

ISSN2454-9940
www.ijasem.org
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tion 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, tech- niques, 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.

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.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions. This work is partially sponsored by the Australian Research Council Discovery grant DP190101079 and the ARC Future Fellowship grant FT190100734.

Data Availability Not applicable.

Declarations

Conflict of interest No.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Code availability Not applicable.

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