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Artificial Intelligence

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Contents

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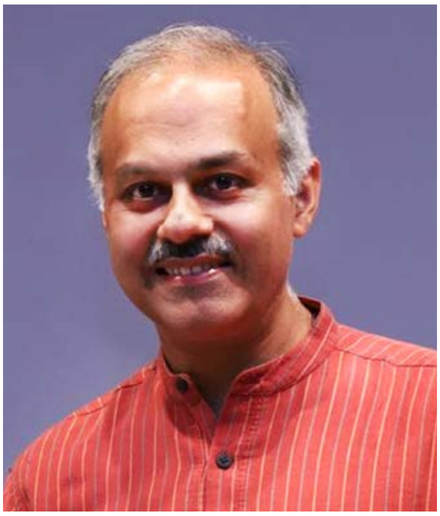
From the Editorial Desk



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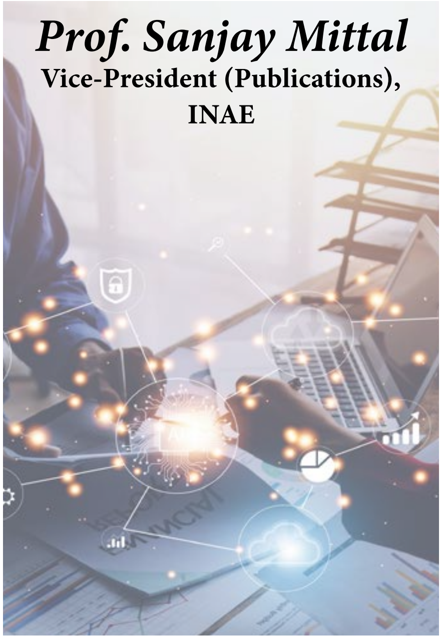

It gives me immense pleasure to bring to you the latest edition of INAE TechFrontier, the quarterly e-magazine of the Indian National Academy of Engineering (INAE), launched on April 20, 2025, during the INAE Foundation Day celebrations. Since its inception, INAE TechFrontier has sought to provide a dynamic platform for sharing ideas, perspectives, and innovations that are shaping the future of engineering and technology.

The journey of Volume I has taken us across a spectrum of emerging and transformative areas. Issue I, "Quantum Technology: India-centric Policy Perspectives," explored the policy landscape and strategic directions shaping India's aspirations in quantum technology. Issue II, "Manufacturing," highlighted the nation's endeavour towards technological self-reliance, innovation, and global competitiveness. Issue III, "Cyber-Physical Systems," examined the growing convergence of computation, communication, and control, while Issue IV highlighted the Sustainability of Civil Infrastructure, an area of increasing significance in an era marked by rapid urbanisation, climate change, and resource constraints. Together, these issues have reflected the breadth and dynamism of contemporary engineering.

The present issue turns our attention to one of the most transformative forces of our time "Artificial Intelligence (AI)". AI is rapidly reshaping the way we think, create, communicate, design, and solve complex problems, with its influence extending across virtually every sector of society and industry. The articles brought together in this issue offer a rich and varied perspective on the evolving AI landscape, covering its applications, opportunities, challenges, and emerging frontiers. Collectively, they underscore the immense potential of AI to accelerate innovation and address complex challenges, while also emphasising the need for responsible, ethical, trustworthy, and human-centric approaches to its development and deployment.

We extend our sincere appreciation to the Editorial Board and Guest Editors for their thoughtful curation of this edition and for their dedicated efforts in bringing together high-quality and relevant contributions. We are equally grateful to all the authors and contributors whose knowledge, experience, and insights have enriched this issue and contributed to its success.

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*Looking ahead, the next issue of INAE TechFrontier, scheduled for September 2026, will focus on **Critical Minerals**, a subject of growing strategic, technological, and economic importance. We warmly invite researchers, academicians, industry professionals, and other interested contributors to share engaging, original, and thought-provoking articles on this important and emerging area. Contributions may be submitted to **publications@inae.in**.*

We hope this issue of INAE TechFrontier will inform, inspire, and stimulate meaningful dialogue on the opportunities and challenges presented by Artificial Intelligence. We look forward to your continued interest, support, and participation as we build this platform for sharing knowledge and ideas that contribute to the advancement of engineering and technology.

Non-invasive Brain-Computer Interfaces for Neuro-motor Rehabilitation

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Abstract

The paper outlines three different methods for Brain-Computer Interface-induced position control of a robot arm to serve as an upper-limb neuro-prosthetic device for patients suffering from Neuro-motor diseases. An outline to the schemes is given along with their relative merits and demerits with respect to control-theoretic performance metrics.

Introduction

Brain-Computer Interfaces (BCIs) refer to a non-muscular channel of communication between a human brain and external computing devices with a motivation to excite the brain states by external stimulus and decode the aroused brain states using brain-imaging equipment. They are currently gaining increasing interest for their purposeful employment in neuro-prosthetic devices, driver safety, assistive robotics, gaming, perceptual-ability assessment of people suffering from brain-diseases and scientific creativity assessment.

This article examines the scope of electroencephalography (EEG)-induced non-invasive BCI systems in the context of neuro-motor rehabilitation. Special emphasis is given to upper-limb prosthesis of people suffering from neuro-degenerative diseases. An artificial humanoid robot arm is employed as the prosthetic aid, and the main focus of the presentation lies in the position control of the arm from its home position to a user-defined target position containing food resources. The robot arm is required to reach the target position, and pick up the food item, and carry it to the

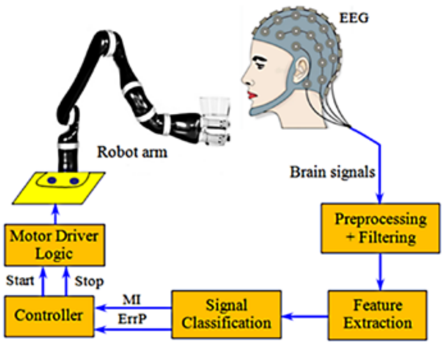

Fig. 1 - EEG-BCI Scheme For Neuro-motor Rehabilitation

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pre-defined mouth-region of the experimental subject (Fig. 1). The challenge in the present research lies in i) precise localization of the target position containing the desired food item by the BCI system, ii) designing a refined control strategy to reach the target position with minimum peak-overshoot (M_p) and steady-state error (SSE), and iii) the entire process should require minimum subjective interaction in order to minimize the cognitive load of the subject. A thorough review of EEG-based BCI for Neuro-motor rehabilitation is available in a recent book chapter[4].

BCI-Induced Position Control Schemes

Three different schemes for BCI-induced position control of a Neuro-motor rehabilitative robot arm are discussed here.

Scheme I

The first scheme utilises 2 brain signals called Motor Imagery (MI) and Error-related Potential (ErrP) to respectively switch on and switch off the motor associated with an individual link of a robot arm[1]. The MI signal, refers to subjective intention to move arms or body parts, resulting in a release of a v-type signal from the motor cortex region of the brain. The falling edge of the v-wave shape refers to Event-Related De-synchronisation (ERD),

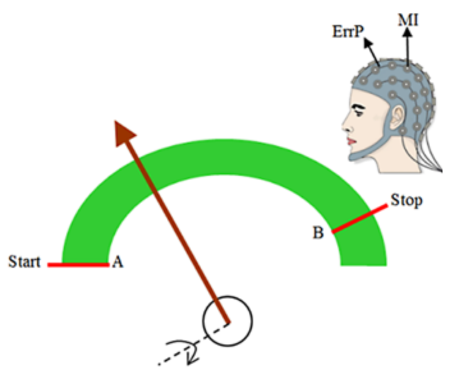

Fig. 2 - MI-ErrP Based Motion Control of A Single-Link Robot Arm

resulting in a decrease in power, and the rising edge, called Event Related Synchronization (ERS), refers to an increase in power until it reaches its previous value before de-synchronization. The v-type MI signal is autonomously liberated from the brain for any motor imagination related task. In Fig. 2, describing motion control of a single link robot arm, we use the MI signal, released by an experimental subject to start moving the arm from the red-marked start position. As the motor is switched on, the robotic link continues moving and the subject watches the movement to stop it at a red marked stop position. When the link crosses the stop position, the ErrP signal referring to the occurrence of error visually detected by the subject is released. The ErrP signal has maximal response from the midline of the brain located around the *Pz* electrode. On detection of the ErrP signal from the *Pz* electrode, the BCI system comes to learn that the robot arm has committed an error (crossing the target point), and so a control command is generated to switch off the motor associated with the moving link. However, due to inertia and latency of the ErrP signal, the robotic link has crossed the target (stop) position. One approach to bring the robotic link back to the target position is to experimentally detect the offset angle measured from the target position. An average of 100 experimental trials of the offset angle is computed to move the robotic link back to the target position[1].

Scheme II

The Scheme I yields a small peak-overshoot and non-zero SSE. One approach to reduce the SSE is to replace the ErrP signal by a P300 signal for the detection of zero-crossing in positional error (desired minus actual angular position). The P300, often referred to as an oddball signal, is released from the parietal lobe of an experimental subject, when he observes or hears an unexpected visual or auditory stimulus. For example, in the present context, the zero-crossing in positional error is an oddball stimulus, and upon the occurrence of zero-crossing of positional error, the P300 signal is released by the experimental subject.

In Scheme II, we employ an MI signal to make the link motor turn on at the start position and detect zero-crossing of positional error at each occurrence of the P300 signal[2]. Once a P300 is detected, the link speed is reduced to half of its last value and its direction is reversed. Such adoption helps in reducing SSE and also peak-overshoot simultaneously. However, it may result in increased settling time in comparison to Scheme I.

Scheme III

In order to reduce SSE, peak-overshoot and settling time jointly, the third scheme is proposed. Here, we can stop the robot arm, at any desired target position by a flickering stimulus using Steady-State Visual Evoked Potential (SSVEP) signal. It may be added here that SSVEP is a frequency modulated signal, liberated from the occipital lobe of the brain on occurrence of a flickering visual stimulus. If the flickering stimulus has a frequency f(= 8 Hz), say, then the SSVEP signal will have a maximum amplitude at 8Hz. To realize a single link position control using SSVEP and MI signal, the experimental subject starts moving the robot arm using an MI signal and stops the robot arm when the robotic link carrying a flickering light stimulus of 8Hz falls on the

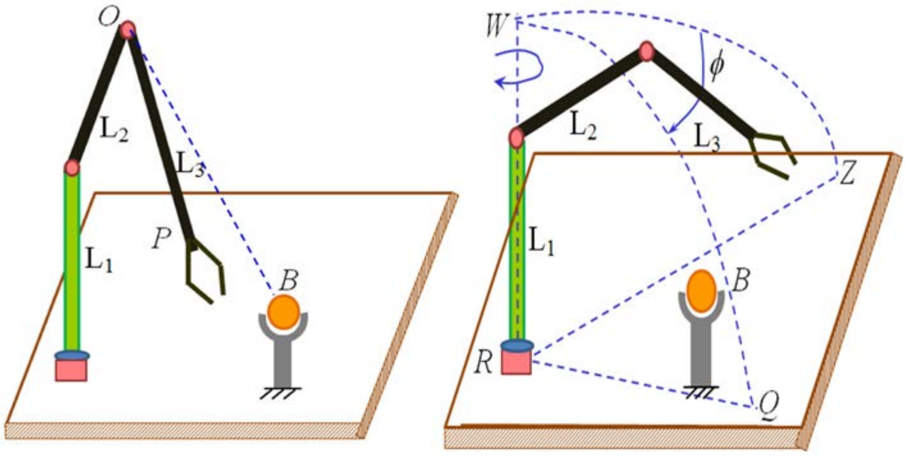

Fig. 3 (a) - 2D Position Control *(b) - Position Control on 3D Platform*

target position. The subject is continuously staring at the target position after he switches on the motor using the MI signal. Naturally, on release of the 8Hz signal from the occipital lobe of the brain, the target position is coincident with the link's current position, and the BCI system commands the robot to stop movement.

The principle adopted by single link MI and ErrP-based position control scheme is extended here for a multi-link robot arm. Fig. 3 (a) introduces the motion control on a 2D platform and Fig. 3 (b) on a 3D platform. Unlike a target position in 1D control, 2D control describes a target position by a straight line, and 3D control describes the target position by a plane. In Fig. 3 (a), the link L3 of the robot arm is lying on the same plane containing a ball. Let OP be the position of the link L3 and OB be the line indicating the position of the ball at point B. If line OP is below line OB, the subject performs a MI, to start moving the link up. Once the link attempts to cross the target line OB, the ErrP is released from the subject's brain and the BCI system commands the robot to stop further movement of the link. As the link has already advanced by a small offset angle, it can be brought back to the location of the ball by controlled movement of the link by an average of the previous 100 offset angle trial values.

In Fig. 3 (b), suppose, the plane RWQ carrying the ball is different with respect to the plane RWZ containing the entire robot arm. Here, 2 cycles of MI and ErrP are required: the first to bring the robot arm aligned with the plane of the ball, and then to move link L3 lying on the plane of the ball to reach the ball. So, here the subject first performs MI to turn the entire robotic link around its waist axis until it attempts to cross the target plane containing the ball. Once the target plane is crossed, the ErrP signal is released by the subject, it is used to stop further movement of the robot arm around its waist joint. Let us assume that the robot arm, by the above operation is lying on the plane of the ball. Now, the situation is like that of Fig. 3 (a), and the process stated above is adopted to align L3 with line OB as in Fig. 3 (a).

The 3-link scheme introduced above like the single link scheme, results in non-zero SSE and small peak-overshoot. To reduce the SSE, the MI-ErrP based scheme is replaced by MI-P300 as introduced for single link control. Alternatively, we can employ an SSVEP based automatic target position identification in a 3D environment and once the target position is localized, we can leave the subject free from participating in the BCI experiment, and employ an autonomous control system to reach the target position identified by the subject, and pickup an object of interest from that position and carry it towards a fixed desired location. For instance, given a number of fruit juice items placed on a table, flickering light beams moving along x, y and z directions in sequence, when attempts to cross the desired fruit juice by the subject, the subject will release an SSVEP signal describing the x, y and z coordinate of the target position containing the fruit juice of his choice. The BCI system on receiving the coordinate of the desired fruit juice, may command the robot arm to reach this position, pick up the fruit juice and bring it towards the subject's mouth region to enable him to sip the fruit juice. The merit of Scheme III includes zero steady-state positional error, no overshoot and above all reduced cognitive load of the subject.

Fig. 4 proposes the complete scheme of 2-loop automated

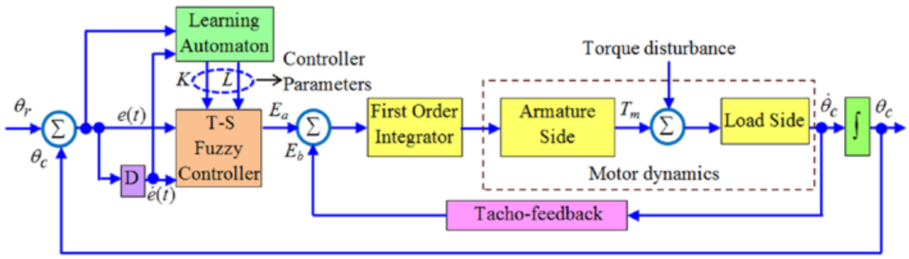

Fig. 4 - Architecture of SSVEP Based Automated 2-loop Position Control Scheme

control where the outer-loop is designed for position control and speed-setting of the inner-loop, whereas the inner-loop is for speed control. The tacho-feedback in the inner-loop enhances the overall stabilization of the system. To keep the system free from external torque disturbances, an adaptive control strategy is proposed in Fig. 4. The control strategy includes a Takagi-Sugeno (T-S) fuzzy controller, which is well-known to be robust for concurrent multiple rule-firing to generate the control command. To keep the system adaptive to torque disturbance, we employ 2 controller parameters K and L which are being tuned by a learning automaton (LA)[3].

Table-I: Results of Performance Analysis

Scheme No.	*SSE*	M_p	*Cognitive Load*
I.	2.10	4.9	5.41
II.	0.20	4.2	5.41
III.	0.018	1.98	3.61

Table-I provides a comparison of the proposed three techniques with respect to three metrics: SSE, M_p and cognitive load. Here cognitive load is measured experimentally using the NASA Task Load Index (TLX) scheme. It is apparent from the Table that Scheme III outperforms Schemes I and II with respect to all three metrics.

Discussion

Apart from the three techniques presented above, there exist a few recent works of great importance on EEG-BCI research. In a recent work[5], the authors aimed at extracting the sign and magnitude of positional error from the brain signals for precise control of an artificial robotic limb. More sophisticated research utilizes both EEG-BCI and a camera-based vision system for autonomous reach and grasping of user-intended objects by a robot arm[6]. Additional works include virtual reality based target-object identification using SSVEP for robot position control[7]. From the control points of view, recent works focus primarily on the model predictive control[8] of artificial limbs, particularly to enable the end-effector to reach a moving target (subject's mouth region) to feed the food item of her interest.

The cortical signals used in EEG acquisition do not carry sufficient information for precise position-control of arms and fingers. Due to this reason, there is hardly any clinical exploitation of EEG-BCI techniques for Neuro-motor rehabilitation. We expect more sophisticated non-invasive means of signal acquisition and advanced signal processing algorithms to capture finer motor intention for position-control of upper limbs and fingers.

Besides position-control applications, EEG-BCI is nowadays being used in gaming[9], motor-learning[10] and color perceptual ability detection[11], and decoding of the scientific potential of creativity of people[12].

Conclusion

MI and ErrP based control is simple with small peak-overshoot and non-zero SSE. To reduce SSE further, the MI-ErrP-based scheme can be replaced by an MI-P300-based scheme. A further improvement in controller architecture for a multi-link robot arm can be realized using SSVEP-based target position selection and autonomous control by LA induced Takagi-Sugeno fuzzy controller.

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Frugal AI for Accessible Healthcare

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Abstract

Integrating Artificial Intelligence (AI) into modern-day healthcare aims to revolutionise diagnostic precision by assisting clinical professionals to cope with increasing medical data workload. However, the current trend of AI development governed by massive "foundation models" has resulted in an accessibility gap. These systems, while being powerful, are data hungry and demand a massive amount of computational resources that are often unavailable in resource-constrained healthcare settings. This article addresses this gap through the concept of Frugal AI; designing intelligent systems while minimizing resource consumption. After establishing the definition of this emerging field, the fundamental principles for achieving computational efficiency are discussed. These are vital for developing computationally efficient AI systems. Subsequently, the industry transition from server-centric processing to deployable, edge-based solutions, is analyzed in the light of real-time performance. A collection of novel architectures, designed for specific clinical requirements, is next discussed spanning lightweight models for mobile health to linear-complexity backbones for real-time applications. This article illustrates that by prioritizing algorithmic efficiency over parameter scaling, advanced diagnostic capabilities can be successfully adapted to resource-limited settings; thereby, connecting technology innovation with accessible patient care.

1. Intelligence Engineering in Healthcare

The history of engineering has been defined by the automation of manual labour. From automating physical tasks, the 21st century makes a shift towards automating cognition, defined by the domain of Intelligence Engineering. The key terminologies surrounding this field are Artificial Intelligence, Machine Learning and Deep Learning. Artificial Intelligence

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Prof. Sushmita Mitra, FNAE, is a senior Professor (HAG) at the Indian Statistical Institute. She was a recipient of the DAAD Fellowship to work in RWTH Aachen, Germany, the IEEE Neural Networks Council Outstanding Paper Award, the CIMPA-INRIA-UNESCO Fellowship, the University Gold Medal, the INAE Chair Professorship, the Fulbright-Nehru Senior Fellowship, and the J. C. Bose National Fellowship. Dr. Mitra is a Fellow of IEEE, TWAS, IAPR, and AAIA, as well as all four national academies of India (INSA, IASc, INAE, and NASI), and a recipient of the J. C. Bose Fellowship Grant 2026. She is the author of more than 200 refereed articles and multiple books. She serves on the Editorial Boards of several reputed international journals. Her research interests encompass data science, machine learning, medical imaging, bioinformatics, and soft computing.

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(AI) is a suite of computational tools for automating decision-making based on data. It refers to the broad field of developing systems capable of mimicking human cognitive functions, such as reasoning or perception. Machine Learning (ML) is a subset of artificial intelligence that represents the shift from deterministic to probabilistic systems. Instead of coding explicit rules, we feed the ML algorithms relevant data related to the task at hand, and the algorithm learns the inherent relationship between them. In this way, the algorithm learns to generalize well by making accurate predictions on unseen data. This is unlike a rigid algorithm that works with hard-coded conditions. Deep Learning (DL)[1] is a specialized subset of ML, inspired by the biological structure of the brain that is driving the current boom in AI. It uses Artificial Neural Networks with multiple layers, (hence the name "deep") to process unstructured data. While a standard ML algorithm needs a human to determine the relevant features for processing, DL approaches extract these features on their own from the raw input data. This reduces the amount of human intervention in the process. Although intelligence engineering has been applied across various sectors, its applicability in healthcare is of utmost importance. Medical data is complex and involve subtle patterns and variations in disease, which are difficult to perceive without assistance. The shift to Deep Learning was needed to extract accurate insights from high-dimensional multimodal input.

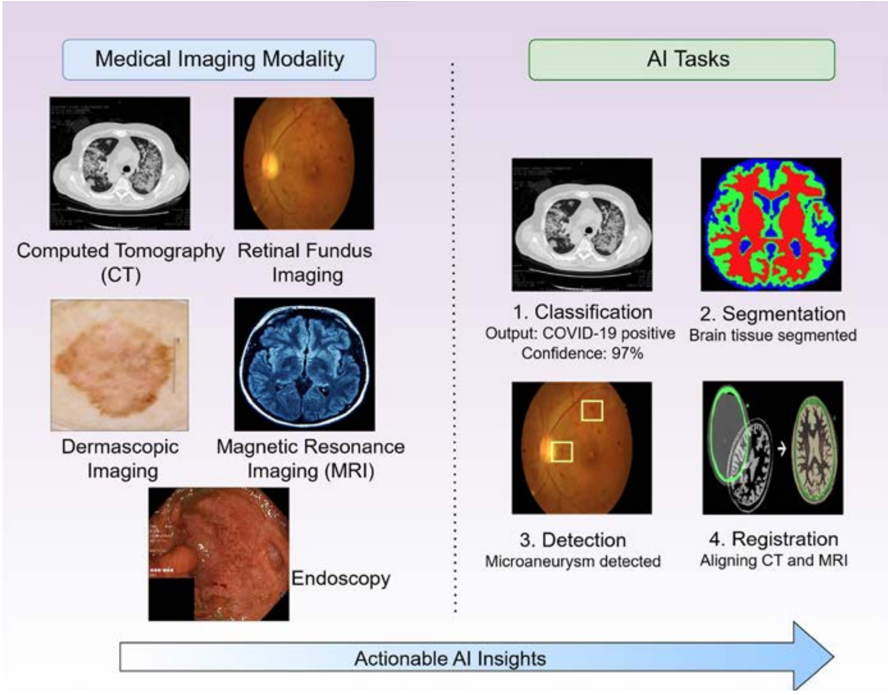

Fig. 1 - Multimodal Image Analysis with AI in Healthcare

Modern machinery in the healthcare sector produces data at an exponential rate. A single patient scan involves hundreds of 2D slices which are analyzed by radiologists to discover anomalies that are often only a few pixels wide. This manual evaluation creates a bottleneck in the diagnostic pipeline. Paying visual attention, manually, degrades over time. This not only slows down the daily throughput but introduces variability in accuracy. AI algorithms process massive volumetric datasets in seconds to filter noise and flag any anomaly. These systems have the advantage of generalization to robustly handle natural variability occurring in different patients. This converts raw input data into a stream of actionable intelligence. The clinical workflow is ideally designed to have a mutual relationship between the system and healthcare professionals by leveraging the strengths of algorithmic precision and human reasoning. In this partnership AI handles the low-level processing load by automatically segmenting organs, calculating tumor volumes and flagging severe cases. This allows the healthcare professional to interpret the clinical significance of the results, relating it with the patient's history and devise a treatment plan accordingly. While AI algorithms provide the speed, humans provide judgement based on algorithmic decisions. The different AI tasks, typically associated with medical image analysis, are illustrated in Fig. 1.

2. Delusion of Bigger is Better

In the present state of Artificial Intelligence, the models are growing exponentially in size. We are in the age of "foundation models", which are huge systems trained using a massive amount of generalized unlabeled data[2]. These models are capable of accurately performing a wide range of diverging task such as understanding natural language, and generating text and images based on user prompts. Rather than developing an AI system from scratch, data scientists use these models as starting point to develop new specialized applications[2]. The size and complexity of these models have grown exponentially over the past decade. BERT[3], one of the earliest Bidirectional

Foundational Models, had 340 million trainable parameters. It was trained using a 16 GB dataset. Five years later, OpenAI trained GPT-4[4] with a 45 GB training dataset and 170 trillion parameters. According to OpenAI, foundation modeling has doubled in computational power every 3.4 months since 2012. Modern FMs, like the Large Language Models (LLMs), are capable of a wide variety of tasks across many domains. This paradigm of foundation modeling has penetrated the field of modern day medical image analysis, changing the way how medical diagnostic tools are designed. Initially, the domain relied on handcrafted features like edge detection or region-growing to detect target anatomical structures, like tumors, from medical images. Although computationally lightweight, they failed to generalize to the unique characteristics corresponding to the target structure(s) across different patients. The approach shifted drastically with the arrival of Deep Learning, specifically U-Net[5], which replaced manually extracted features with learnable ones. The network now could identify the region-of-interest by learning from examples rather than relying on specific rules. However, this led to a new bottleneck, *data scarcity*. Medical datasets are often small-sized due to the prohibitive cost involved in obtaining manually annotated images. Furthermore, the ground truth often becomes subjective, as inter-rater variability can lower the quality of the labeled data.

Transfer learning[6] has gained prominence as a solution to data scarcity. Here the models, pre-trained on extensive natural image datasets, are adapted for subsequent medical image analysis tasks. Although effective, this approach proved to be a *square peg in a round hole* solution; mainly, due to the domain gap between natural and medical images. The need to bridge this gap led to a shift to the current era of foundation models in the healthcare domain. By fine-tuning a large backbone in medical archives, such as MedSAM[7], these models generalized well across almost all organs.

However, solving the data issue with this technology created deployment problems due to accessibility crisis. For low or middle-income countries like India, it created a barrier to the wide acceptance of modern AI technologies in healthcare centers. The medical infrastructure, specifically in the Tier-2 or Tier-3 cities, operates with budgetary restrictions. They rely on mid-range laptops that lack huge Video RAM (VRAM) to load and execute a billion-parameter deep learning model like MedSAM. Relying on cloud servers for heavy computations is often impractical due to poor network issues in rural areas and strict data privacy regulations of the patients.

Eventually, it leads to a digital divide where the smart foundation models become inaccessible to resource-constrained settings, which handle the majority of the patient load. This highlights the urgent need for **Frugal AI**, a deep architecture that provides a precise diagnosis with a reduced computational burden. Table-1 presents a summary of the structure of the article. This structural flow reflects the real-world engineering lifecycle of Frugal AI, progressing from the identification of hardware constraints, through the application of fundamental and novel efficiency techniques, to final clinical deployment and mitigation of subsequent challenges.

3. Frugal AI: Engineering for Constraints

Frugal AI (Fig. 2) is the practice of developing AI systems with maximum efficiency while minimizing resource consumption[8]. This aligns with the sustainability goals and encourages the wide acceptance of AI technologies in society. It

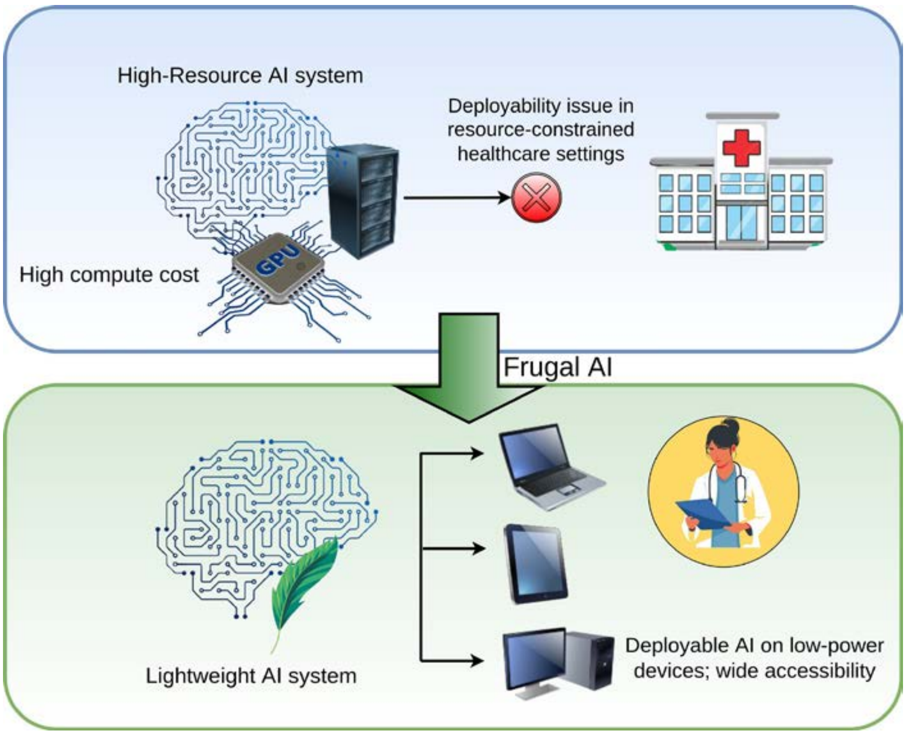

Fig. 2 - Bridging AI Accessibility Gap in Healthcare with Frugal AI

Table 1: Mapping the Article Structure to the Frugal AI Lifecycle

Article Section	Core Concepts & Technologies	Role in the Accessible Healthcare Framework
Sec. 3: Delusion of Bigger is Better	• Hardware limits in Tier-2/3 Clinics • Resource-heavy Foundation Models	Establishes the urgent need to shift from massive, cloud-dependent models to deployable systems optimized for budget constraints.
Sec. 4: Engineering for Constraints	• Model Pruning • Quantization • Knowledge Distillation	Provides the fundamental engineering techniques used to compress model size, reduce memory footprints, and accelerate inference.
Sec. 4.1: Frugal AI in Healthcare	• Offline Mobile Screening • TinyML (Biosensors) • Generative Edge AI (Liquid NNs)	Highlights real-world clinical deployment paradigms, enabling privacy-preserving, zero-latency diagnostic assistance directly on edge devices.
Sec. 4.2: Our Contribution	• Resource-aware Attention • Spectral-spatial Fusion (Wavelets) • Linear-complexity (xL-STM/Mamba) • Prompt-driven Token Pruning	Details our specific architectural frameworks that re-engineer the AI pipeline for high-dimensional medical data without quadratic bottlenecks.
Sec. 4.3: Challenges of Frugal AI	• Domain Generalization • Explainable AI (Black Box Opacity) • Federated Learning	Outlines the vital engineering and ethical hurdles required to ensure deployable models remain robust and trustworthy across diverse clinics.

involves sophisticated techniques like Model Pruning[9], Quantization[10], and Knowledge Distillation[11], as illustrated in Fig. 3. The goal is to provide high-level inference on edge devices without constant reliance on cloud servers.

Model Pruning refers to removing redundant edges, that do not have a significant contribution to the neural network output. This helps reduce the parameter count without affecting the learned knowledge. Deep learning models perform their computation with 32-bit floating-point precision. Quantization reduces these calculations to lower precision formats, like 8-bit integers, shrinking the memory footprint by nearly 75%. Additionally, modern-day processors use a high-speed integer arithmetic unit to perform the computations using reduced-precision weights, thereby reducing latency. Finally, knowledge distillation trains a small student network to mimic a larger network like a foundation model. This helps the lightweight model to absorb the complex reasoning process of the large teacher network; thereby, allowing it to generalize better than when trained in isolation.

3.1 Frugal AI in Healthcare

Nevertheless, Frugality must not compromise precision in a high-stakes field like healthcare. To address this requirement, industry is shifting towards hybrid architecture systems that integrate the precise edge-detection capabilities of Convolutional Neural Networks with the global context-awareness of lightweight attention mechanisms. Such a "best of both worlds" approach enables the model to function on standard hardware without overlooking essential pathologies. This architectural efficiency addresses three essential factors concerning Frugal AI, *viz.* Cost, Speed of Inference and Privacy.

The approach is driving a new era of live clinical applications beyond theoretical models. In rural India, companies have deployed offline AI for real-time screening of

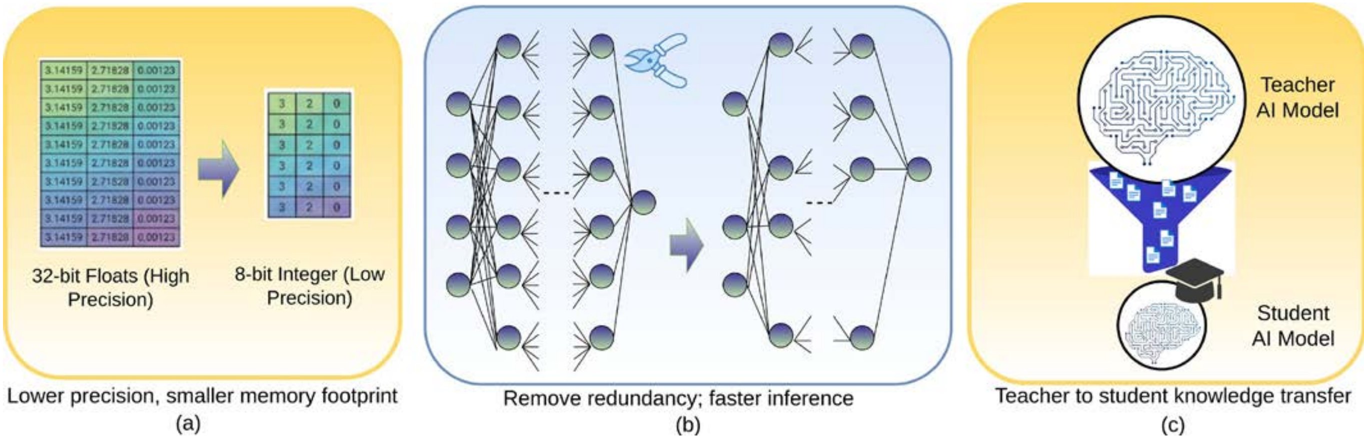

Fig. 3 - Primary Methods in Frugal AI for Creating Efficient and Deployable Models

diabetic retinopathy on smartphone-based fundus cameras. These devices check for retinal lesions in real-time, without needing internet connectivity. The field of TinyML runs AI models on low-power devices like microcontrollers. This enables embedding of lightweight architectures on wearable biosensors. For instance, smartwatches can monitor vital signs like oxygen saturation (*SpO_2* level), heart rate, and sleep patterns. They flag anomalies like irregular heartbeat and raise an alarm. Medical diagnostic companies are integrating frugal AI into their portable X-ray and ultrasound machines for automated detection of anomalies, particularly where deploying massive GPUs is infeasible.

The field of TinyML is rapidly expanding into Generative Edge AI. Liquid Foundation Models[12] lead this paradigm shift. They employ biologically inspired Liquid Neural Networks[13] specifically designed for edge devices. These models process data with reduced memory footprints; thereby, bringing the powerful reasoning capabilities of Foundation Models to edge devices without relying on cloud-hosted large models. The implementation of privacy-preserving medical assistants, operating entirely in offline mode, makes it a critical evolution for the healthcare industry. This also mitigates the latency and data leakage risks associated with cloud transmission.

National initiatives like Ayushman Bharat Digital Mission (ABDM)[14] aims to integrate fragmented healthcare services across the country into a unified digital network. However, realizing the vision of AI for all requires overcoming infrastructural bottlenecks in Tier-2 and Tier-3 cities, cloud-dependent processing is unfeasible due to limited internet bandwidth. Frugal AI serves as the critical engineering bridge in this landscape. Several successful industrial and state-led deployments such as the integration of AI-driven digital X-rays to automatically and robustly detect Silicosis in remote, resource-constrained mining regions of Rajasthan have been carried out[15]. Furthermore, leading medical R&D hubs are increasingly focusing on embedding lightweight AI directly into portable acquisition hardware. These industrial applications are ensuring AI-assisted diagnostic screening can be achieved affordably and reliably at the grassroot level.

3.2 Our Contribution

Our research focused on designing a new computational pipeline, by presenting novel frameworks that enhance diagnostic accuracy while reducing resource utilization. This section highlights our four-pronged strategy for Frugal AI: (1) creating resource-aware architectures that simulate human attention; (2) utilizing spectral domains for robust feature learning with fewer parameters; (3) overcoming quadratic computational complexity by integrating linear models for volumetric data analysis, and (4) identifying and eliminating redundant computations for faster inference. These collectively illustrate that lightweight models can attain state-of-the-art performance on standard hardware.

Architectural Frugality: Traditional 3D medical image segmentation is often parameter-heavy and slow. To address this, a resource-aware attention mechanisms were developed[16]. In-stead of processing entire volumes, the architecture employs a global-context-aware strategy to select relevant information, ensuring that only relevant data is processed in the model pipeline. The model achieved superior segmentation performance on a variety of medical images, with lower computational complexity than standard 3D backbones.

Cross-domain Intelligence: Standard segmentation models downsample the images to reduce computational load, resulting in the loss of fine-grained textural details. The hybrid Convolutional Transformer with Wavelets[17] retains the lost information *in lieu* of adding heavy computational blocks. By processing both spatial and spectral features at the same time, it became possible to obtain state-of-the-art accuracy in defining complex abdominal organs with fewer parameters.

Overcoming Quadratic Bottleneck: Despite being state-of-the-art, Vision Transformers often become impractical for handling huge 3D medical image volumes, due to their quadratic computational complexity. The Extended Long Short-Term Memory (xLSTM)[18] and Mamba[19] were adapted for segmentation tasks[20], [21], [22]. This effectively addresses the quadratic bottleneck problem with their linear computational complexity. It drastically reduces the computational barrier, enabling faster processing of volumetric data.

Eliminating Redundancy: Standard deep learning models waste a lot of computational resources in processing the large number of background pixels found in medical images. A prompt-driven adaptive token pruning framework was introduced[23] to identify and discard up to 55% of redundant tokens. This resulted in a massive reduction in computational load during inference, leading to faster diagnostic times and lower energy consumption.

Each model in the listed suite of architectures is tailored for specific clinical applications. For instance, models[21], [22] are optimal choices for deployment on edge devices; by delivering the highest segmentation accuracy with lowest parameter count and memory footprint. For real-time applications, like image guided surgery, model [20] can be preferred due to its high inference speed. Finally, model[17] is suitable for detailed offline analysis on centralized servers, with its top quality segmentation output.

3.3 Challenges of Frugal AI

While the shift to frugal AI democratizes healthcare, it presents engineering and ethical issues that must be resolved for effective implementation, as illustrated in Fig. 4. One of the significant challenges is the domain shift problem. Large foundation models become a generalist (jack-of-all-trades) by learning huge variance in medical data distributions. However, Frugal AI models are specialized in specific tasks. The biggest hurdle is to ensure robustness when faced with different types of data. Variations in scanner physics or image acquisition protocols severely impact the performance of lightweight models. Incorporating domain generalization helps frugal models adapt to unseen data, without requiring to be retrained each time.

The black box nature of the model raises concerns about trust and interpretability; thereby, limiting their adoption to actual clinical scenarios. Integrating explainable AI to these models provide a radiologically relevant justification behind the decision-making process. This enhances clinician trust in the assistive intelligence framework.

Protecting patients' information is of prime importance while training these models. Federated Learning[24] offers a solution by training the AI algorithms across different hospitals; without transmitting patient data to a central server or any other shared locations. However, transmitting heavy models across different health centers incurs significant communication overhead.

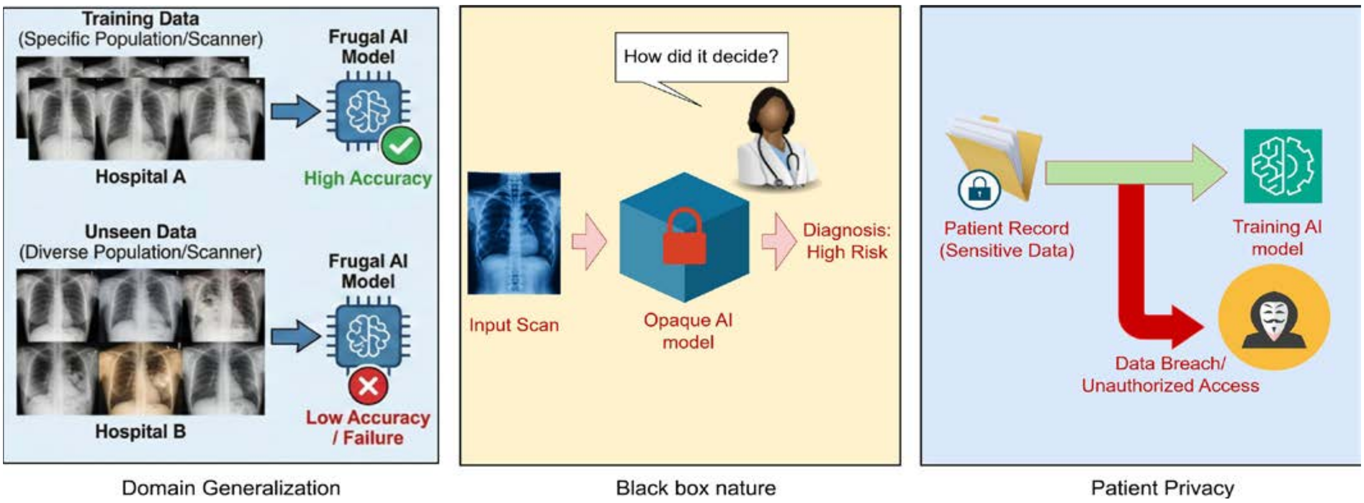

Fig. 4 - Critical challenges for adopting Frugal AI in healthcare, viz. *domain generalization, black box nature of AI models, and protecting patient data during training.*

Lightweight models are comparatively cheaper to transmit over hospital networks involving limited bandwidth. Designing distributed systems is of prime importance, so that the models can have stable training in a decentralized setting.

3.4 Practical Implementation and Industrial Adoption

The clinical deployment of Frugal AI theoretical framework requires addressing engineering and logistical challenges. A primary implementation hurdle is interoperability within existing hospital networks. Medical facilities rely on Picture Archiving and Communication Systems (PACS) and the DICOM standard. Parameter-heavy foundation models typically require off-site cloud processing or on-premises GPU clusters, creating bandwidth bottlenecks and integration complexities. In contrast, frugal architectures are highly scalable; their minimal memory footprint allows them to be containerized and deployed directly onto a hospital's standard IT infrastructure, ensuring seamless interoperability. Major medical device manufacturers are embedding lightweight AI directly into the acquisition hardware itself, such as ultrasound probes, portable X-ray machines, and MRI scanners. Heavy computation drains the limited battery life of portable diagnostic tools and generates heat that can degrade sensor performance. Frugal AI ensures that continuous, real-time diagnostic screening operates safely within the thermal and energy budgets by reducing the computational complexity.

Conclusion

Advancement in deep learning often equates performance with model size. However, for a wide adoption of AI methods from research labs to real-world clinical settings requires, particularly in resource-constrained environment like India, a new paradigm called Frugal AI. This paradigm shift ensures that high diagnostic precision can be achieved at low computational costs. New innovations suggest that lightweight models can surpass their heavy counterparts in terms of performance; thereby, challenging the general notion that high-performing AI models need massive infrastructure. By reducing the hardware requirements, Frugal AI enables sophisticated diagnostic tools to work on standard computing systems in Tier-2 cities and remote clinics. This effectively bridges the gap between technological innovation and universal healthcare access.

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Artificial Intelligence and Scientific Research

A Strategic Review for Engineering & Technology Leaders

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Abstract

This paper examines the growing role of Artificial Intelligence (AI) as a foundational instrument of scientific discovery rather than a peripheral aid to research. It analyzes how AI is reshaping the research and development continuum through literature synthesis, hypothesis generation, simulation, experimental design, autonomous laboratories, digital twins, and productization. Drawing on developments in materials science, life sciences, behavioural science, and sensing, the paper reviews current advances and emerging trajectories. It further situates these developments within India's evolving policy and innovation ecosystem, and argues that robust governance, reproducibility, equity, and biosecurity frameworks are essential to the responsible and strategic advancement of AI-enabled science.

Introduction

Science has always advanced through instruments that expand what humans can observe and test. The telescope transformed astronomy, the mass spectrometer revealed molecular structure, and genome sequencing made biology legible at scale. Artificial intelligence is emerging as the next such instrument, but unlike earlier tools, it is diffusing across fields with unusual speed and breadth.

The Nobel Committee's 2024 recognition of AI-related work confirmed what researchers already understood. Hopfield and Hinton were honoured for the physics of neural information processing[1,2], while Baker, Hassabis, and Jumper were

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recognized for solving the long-standing protein-folding challenge [3]. That these prizes spanned disciplines in the same year signals a larger shift: AI is no longer a specialist branch of computer science. It is becoming a shared language and method of discovery across the sciences.

This paper addresses five questions relevant to leaders and practitioners navigating that transition:

- Where, precisely, can AI contribute to scientific research?
- What has already been achieved at the frontier?
- What might the next decade bring?
- What is India doing, and what more is needed?
- What safeguards must accompany these capabilities?

The sections that follow draw on the authors' experience, published evidence, and policy documents to answer them.

1. Where Can Artificial Intelligence Contribute to Scientific Research?

The R&D value chain spans at least seven phases, and AI is already affecting each of them [4]. Its importance lies not only in faster problem solving but also in better problem selection. By scanning papers, patents, experimental records, and funding signals, AI can detect weak patterns that are too diffuse for individuals or even teams to see consistently. This helps researchers anticipate promising directions earlier rather than respond after a field has already shifted.

The broader shift is from simply doing more research to doing more consequential research. In that sense, AI increasingly acts as a strategic partner that sharpens judgment about what is worth pursuing as much as it improves speed. It also helps organizations allocate scarce funding, laboratory capacity, and expert attention toward the questions most likely to generate outsized scientific or societal value.

1.1 Literature Synthesis and Hypothesis Generation

Novel ideas usually begin with a researcher absorbing an enormous and fragmented literature. Large language models and knowledge-graph systems now ingest, connect, and summazise that literature at a scale no human team can match. More importantly, they can surface gaps, expose cross-disciplinary links, and propose hypotheses that are concrete enough to test, making early-stage scientific reasoning faster and broader.

1.2 Experimental Design, Active Learning and Autonomous Laboratories

Classical design-of-experiments remains valuable but is labour-intensive. Active learning can adaptively choose the next experiment to reduce uncertainty, and Bayesian optimization can compress the number of trials required, lowering time and cost. Coupled with robotics, these methods enable the self-driving laboratory, where AI plans and executes synthesis, measurement, and analysis with limited human intervention. Such systems are already beginning to move work that once took months into cycles measured in days.

1.3 Simulation and Surrogate Modelling

High-fidelity simulation in areas such as quantum chemistry, structural analysis, fluid dynamics, and climate science is computationally expensive. AI helps by building surrogate

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models, using physics-aware learning, and introducing symbolic or interpretable approaches that preserve scientific usefulness. The aim is not speed alone, but faster insight that remains trustworthy enough for engineering and scientific decision-making.

1.4 Data Analysis & Pattern Recognition: From Prediction to Prescription

Scientific and industrial systems now generate data at massive scale, from genomes and climate observations to manufacturing and infrastructure sensors. AI methods, especially deep learning, are turning such data into digital twins: virtual representations of people, machines, infrastructures, and even planetary systems. By combining sensor streams, historical records, and simulations, these twins support anomaly detection, forecasting, personalization, and scenario testing across domains ranging from maintenance and fault diagnosis to precision medicine [5-9].

The deeper transition is from prediction to prescription. Digital twins increasingly sit inside closed-loop systems that combine optimization, constraints, and causal reasoning. Large language models can serve as cognitive interfaces for these systems by generating scenarios, interpreting outputs, and coordinating agentic decisions [9-11]. This pushes twins toward self-optimizing cognitive systems rather than passive mirrors of reality.

1.5 Prototyping and Productization

Generative AI is also accelerating the move from concept to prototype across design, manufacturing, regulation, and quality assurance. Design platforms can explore large numbers of geometric options rapidly, while text-to-CAD and image-to-3D tools shorten the path from idea to draft model. AI-assisted simulation predicts structural, thermal, or fluid behaviour before fabrication, and digital twins can reveal production bottlenecks before physical setup. When regulatory and quality systems are added, organizations that use AI end-to-end can operate on very different time scales from those applying it only in isolated stages.

2. State of the Art Today

2.1 Materials Science: Discovery & Deployment at Scale

Google DeepMind's GNoME identified 2.2 million new crystal structures, including 380,000 predicted to be stable [12,13]. Lawrence Berkeley's A-Lab then autonomously synthesized dozens of new materials in days, validating the broader direction [14]. Together with systems such as Microsoft's MatterGen and MatterSim [15], these efforts show that AI-driven materials discovery is moving from theory to deployed workflow.

AI is not only enabling the discovery of new materials; it is also reshaping multi-material and chemical product development in consumer industries. Sequential workflows—from brand brief to launch—are being replaced by more parallel, intelligence-driven processes that reduce cost and expert bottlenecks. Large firms such as Nestlé, Unilever, and Mondelēz are investing in this stack, while more specialized platforms like Bettrlabs' Lab.new are helping smaller firms and founders' access similar capabilities at scale [Please refer to the sidebar/illustration].

2.2 Life Sciences: The AlphaFold Revolution

AlphaFold2 effectively solved the long-standing protein-folding problem with near-atomic accuracy and quickly became one of the most consequential AI contributions to biology [16,17]. DeepMind and EMBL-EBI released structures for roughly 200 million proteins, opening access for researchers globally [17]. AlphaFold3 extended the framework to DNA, RNA, and ligands, with implications for drug discovery, vaccine design, and enzyme engineering [18-21].

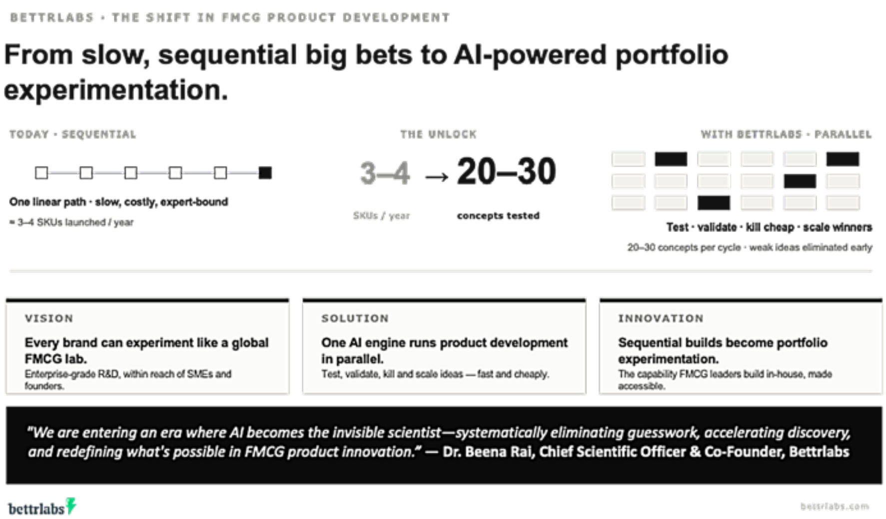
More broadly, AI is reshaping life sciences through diagnostics, therapeutic design, and clinical reasoning. Systems in radiology, dermatology, and pathology have reached physician-level or better performance in specific tasks, and recent reasoning models have shown strong results when diagnosing from electronic health records [22].

2.3 Behavioural Science

Behavioural and design sciences highlight that scientific systems are not only technical but human. AI can analyze large-scale behavioral data to model uncertainty, adaptation, and decision patterns, enabling digital twins of human behaviour and more adaptive interventions. Design science extends this by using AI to address complex challenges in areas such as workforce design, mental health, finance, and customer engagement. Together, these efforts suggest a frontier in which AI is used not only to optimize systems but also to improve wellbeing, judgment, and societal outcomes.

2.4 AI as Autonomous Researcher: The Emerging Frontier

The most provocative frontier is the prospect of AI systems that can conduct much of the research cycle: reviewing literature, forming hypotheses, designing experiments, interpreting results,



and drafting outputs. Early systems such as ChemAgents, which coordinate specialized agents for reading, planning, computation, and robotic execution, illustrate the architecture of this possibility [23]. Reported laboratory evaluations have also shown dramatic efficiency gains in narrowly defined biological protocols [24]. These systems still require close validation and oversight, but they indicate that the scientist's role may shift progressively from manual execution toward strategy, quality assurance, and ethical supervision.

3. Opportunities for the Future

Looking ahead, several convergences are likely to shape the next decade of AI-enabled scientific research.

3.1 The Self-Driving Laboratory at Scale

Today's autonomous laboratories are mostly domain specific. A near-term opportunity is to build modular, networked versions capable of handling multi-step and multi-domain research problems with limited human intervention at each stage. If such systems mature, they could broaden access to advanced experimentation beyond elite labs and reduce the role of geography in scientific opportunity.

3.2 AI for Design – Generalizable Inverse Design Using Generative AI

Inverse design across materials, sensing, circuits, and engineering systems is high-dimensional, non-linear, and often computationally prohibitive. Generative AI offers a path to learn mappings between design variables and system responses so that feasible designs can be produced more directly. Evidence already exists across cellular structures, airfoils, fluid-structure interaction, plasmonics, antennas, circuits, and metasurface systems [25-34]. For broad industrial adoption, however, these systems must also become interpretable, robust, and causally informed. A shared framework supported by open datasets across institutions could make AI-driven design more scalable and accessible.

3.3 Foundation Models for Science

Just as general language models transfer across text tasks, foundation models trained on scientific data are beginning to generalize across scientific tasks. Models trained on proteins, molecules, simulations, and experimental measurements suggest a future in which one large pre-trained system supports many downstream applications. In sensing, sensor-specific foundation models follow a similar logic by learning reusable latent representations that separate perception from cognition and improve accuracy, latency, and interpretability [35,36].

3.4 Human-AI Scientific Collaboration

The most productive near-term model is likely to be collaboration rather than replacement. AI can survey literature, suggest experimental variants, detect inconsistencies, and maintain documentation, allowing scientists to concentrate on framing, judgment, and synthesis. Designing effective collaboration protocols—including trust calibration, override mechanisms, and credit allocation—will itself be an important research agenda. In practice, the quality of this partnership will depend not only on model capability but also on workflow design, transparency, and the training scientists receive in using these systems critically.

3.5 Convergence with Quantum Computing

Quantum computing could eventually simulate certain quantum systems far faster than classical machines, with implications for materials, drugs, and cryptography. Early demonstrations and industry road maps suggest that the most important impact may come from combining quantum computation with AI-based optimization, making this a significant frontier for computational science.

3.6 The Human Element: Agency and Purpose

For now, the aims of science still come from humans: the disease to target, the material property to improve, the conjecture worth exploring. AI may become increasingly powerful in searching solution spaces, but intent remains human. It is possible to imagine future systems that generate their own goals at the level of laboratories, organizations, or societies, yet that moment has not arrived. Until then, agency and responsibility remain firmly human concerns.

4. India Context: Actions Being Taken

India is not a passive observer of these developments. Government policy, institutional investment, and industry participation are positioning the country to contribute to and benefit from AI-enabled science.

4.1 AI for Science and Engineering

The Anusandhan National Research Foundation's AI for Science and Engineering Mission seeks to make AI a core layer of India's research ecosystem through work on neural operators, physics-informed learning, and domain-specific foundation models. It targets areas such as climate science, materials, biomanufacturing, astrophysics, and medical imaging, while also emphasizing interoperable datasets, models, and infrastructure through an open ecosystem approach [37].

4.2 Research Ecosystem

The government has established AI Centers of Excellence in healthcare, agriculture, and sustainable cities in New Delhi, and announced a fourth for

AI-Enabled Science: TCS Research at the Frontier
An interview with the Dr Harrick Vin: Chief Technology Officer, Tata Consultancy Services

Q1: TCS Research has been making significant investments in AI for science. Where are the most exciting frontiers you are pursuing today?

"We are working across several high-impact directions simultaneously. In AI for design, our generative AI work is fundamentally recasting drug discovery—moving from search-driven screening to design-led molecule engineering, including de novo generation, multi-parameter optimization, and synthetic feasibility prediction. We are extending this design-first approach beyond molecules to manufacturable industrial processes through our process and control system synthesis work. In parallel, we are building Sensor-Specific Foundation Models that learn reusable, application-agnostic representations across sensing modalities—with early evidence of improved accuracy, latency, and interpretability. And in astronomy, we are co-developing multimodal foundation models with NCRA–IUCAA to unlock complex observational archives and catalyze AI-driven astronomy research in India and globally."

Q2: TCS Acceleron has been described as a distinctive approach to AI-assisted research. What makes it different from other AI research platforms?

"The distinction lies in a deliberate design principle: Acceleron is not an autonomous researcher—it is a co-creation system where human judgment remains central. Researchers actively steer the process, guiding direction, assessing novelty and feasibility, and validating outcomes. Acceleron identifies weak signals across fragmented scientific sources, supports impact-aware exploration, and refines hypotheses through a generator–verifier loop. Our early system, IRIS, has already demonstrated that researchers deeply value this ability to shape hypothesis generation rather than passively consume AI outputs. This shifts scientific effort from volume to high-impact, judgment-driven exploration—and that is a fundamentally different proposition from what most AI research tools offer today."

Q3: Where do you see AI and quantum computing converging, and what is TCS Research's broader philosophy as it navigates all these frontiers?

"Quantum computing represents a natural convergence point for AI in science. We are pursuing a hybrid strategy spanning quantum optimization, quantum machine learning, and quantum chemistry, reinforced by our role in the Andhra Quantum Valley initiative. But across all these efforts—AI for design, foundation models, human–AI collaboration, and quantum convergence—there is one consistent principle: AI is an amplifier of human judgment, not a substitute for it. This is an explicit design choice in our broader hybrid-intelligence agenda. The most transformative science will emerge not from AI acting alone, but from AI and human expertise working in deep, purposeful collaboration."

Education in Budget 2025 [38-41]. The National Mission on Interdisciplinary Cyber-Physical Systems has also created innovation hubs that connect AI, automation, and physical systems [42]. Major research institutions are simultaneously expanding AI-driven work across scientific domains.

4.3 Industry Engagement

Industry engagement is also growing. Aurigene, a Dr. Reddy's subsidiary, introduced an AI/ML-enabled drug discovery platform in 2024 that reportedly shortens development timelines [43]. Many Indian pharmaceutical firms are now testing generative AI applications, and the market is expected to expand rapidly [44,45]. In manufacturing, AI is already being used for maintenance, quality, and process optimization, while India's IT sector is increasingly redirecting its data and software strengths toward interdisciplinary scientific research.

4.4 India and Frontier Models

At the same time, frontier scientific capability increasingly appears tied to the most advanced models, which remain concentrated among a small number of corporations and countries. Although India has articulated ambitions for AI investment since the 2017 AI Task Force, domestic efforts remain

Scaling Responsible AI for Science: A Conversation with Dr. Sachin Lodha, Head of Research, Tata Consultancy Services

Q1: TCS Research has been investing heavily in AI for Science. How is this translating into real-world, deployed capability rather than just research prototypes?

"We are deliberately moving beyond isolated innovation to embed AI into production-grade, end-to-end R&D pipelines. Across life sciences, healthcare, materials, chemical systems, engineering design, manufacturing, and sustainability, we are combining simulation, data, and decision systems to create closed-loop, reproducible, and audit-ready workflows. This is not AI as an experiment—it is AI as an operational substrate for science and engineering, deployed in real environments and delivering measurable outcomes."

Q2: TCS has deep academic and national ecosystem partnerships. How are these shaping your AI-for-Science agenda?

"Our ecosystem partnerships are central to how we translate research into national impact. Our long-standing collaboration with IIT Kanpur on Integrated Computational Materials Engineering has been extended by making the PREMAP platform available to academia, enabling faster, simulation-driven materials and process research. More recently, as a partner in the AI for Sustainability CoE at IIT Kanpur—under the AIRAWAT Research Foundation—we are applying AI, remote sensing, and digital twin technologies to urban systems. This enables scenario-driven planning for air quality, flooding, energy use, and climate resilience at city scale. These are not peripheral engagements—they are mission-aligned collaborations directly contributing to India's national priorities."

Q3: Governance and trustworthiness of AI systems is an increasing concern globally. How is TCS addressing this in its AI-for-Science work?

"Trustworthiness is not an afterthought for us—it is a design principle. We have developed TrustEE, our AI assurance framework, specifically to build and operate trustworthy, auditable, and policy-compliant AI systems. TrustEE operationalizes requirements such as model reliability, explainability, data provenance, bias detection, and lifecycle governance—embedding assurance directly into AI pipelines from the outset. As AI moves deeper into high-stakes scientific and engineering domains, this kind of rigorous governance infrastructure becomes not just desirable but essential."

Q4: How do you see AI changing the everyday practice of scientific research, and what does the future of scientific work look like at TCS?

"We are advancing a fundamentally different model for scientific work—one where AI is embedded into everyday research practice rather than used as an occasional tool. Platforms like Acceleron enable tightly integrated, continuous workflows spanning exploration, hypothesis generation, experimentation, and validation. This shifts scientific work from linear execution to iterative, AI-assisted inquiry. Researchers are freed to focus on what humans do best—judgment, validation, and direction-setting—while operating at significantly greater scale and speed than was previously possible. Taken together, our actions reflect a deliberate commitment to scalable, responsible, and impact-driven AI that is embedded in the very practice of science and engineering."

modest relative to global leaders. Current work, including efforts such as Sarvam AI, is important for linguistic and cultural adaptation, but sovereign capability for science in strategic sectors such as defense, space, and national security will likely require much larger and more deliberate investment [46].

5. Safeguards and Governance

Capabilities that accelerate discovery can also amplify risk. Governance therefore has to be treated as a strategic layer of AI-enabled science, covering automation levels, model reliability over time, intellectual property controls, access to data and compute, and the institutional partnerships needed to manage these issues responsibly.

5.1 Biosecurity and Dual-Use Research

Tools that predict proteins and biological function can also lower barriers to misuse, including pathogen design [47-51]. In response, international efforts in 2025 advanced shared safety commitments, pre-release evaluation practices, and synthetic nucleic acid screening [52,53]. India, as a major pharmaceutical and biotechnology producer, has a direct stake in how such governance develops.

5.2 Ethical Research and Data Governance

Questions of data provenance, reproducibility, attribution, and bias remain central. The EU AI Act has established a risk-based approach for high-risk uses, while India's emerging framework points toward a lighter-touch model supported by dedicated governance and safety institutions [54]. For research settings, this means governance must extend beyond compliance checklists to routine practices for documentation, auditability, and post-deployment monitoring.

5.3 Compute Access and Digital Equity

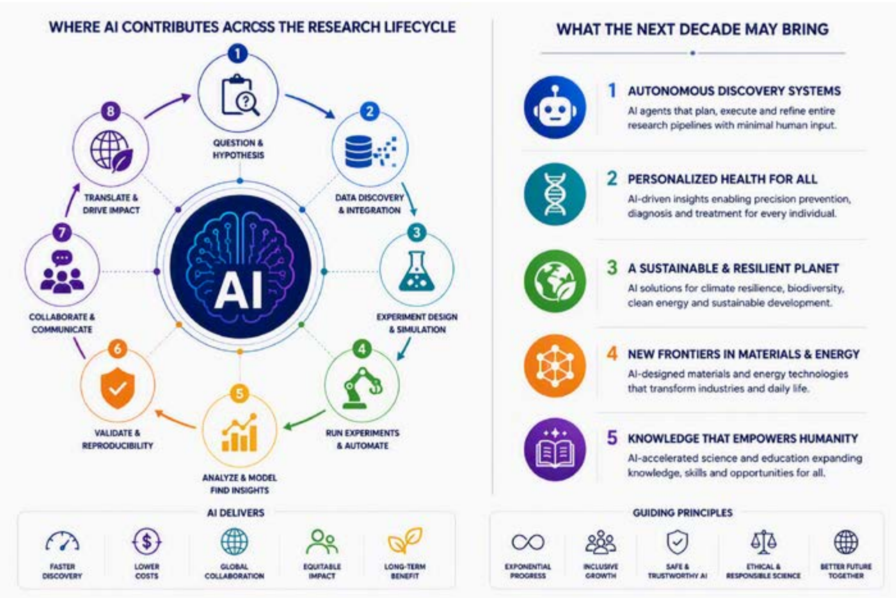
Without deliberate intervention, concentration of compute can translate into concentration of scientific opportunity. India's IndiaAI Mission and international efforts such as the Network of AI for Science Institutions are important responses to this structural risk.

5.4 Open Science and Reproducibility

Open datasets, models, and benchmarks remain essential for reproducibility, and AlphaFold's open-access model is a strong demonstration of how openness can accelerate global scientific use.

5.5 Cybersecurity in Research Infrastructure

Self-driving laboratories and connected research systems enlarge the attack surface for adversaries, making cybersecurity and the protection of scientific data and intellectual property increasingly important.



6. Recommendations and Conclusions

AI has crossed a threshold in science. It is becoming part of the substrate of discovery rather than a tool used only for bounded tasks however, the implications differ by stakeholder:

6.1 For Individual Researchers

Researchers should adopt AI with domain-specific checklists and validation habits while preserving the foundational practices—literature review, hypothesis generation, mentorship, and methodological understanding—that build durable scientific judgment.

6.2 For Institutions

Institutions should ensure access to skills, tools, and safeguards, developed practical "AI for Researchers" curricula, encourage collaboration across AI-native and non-AI-native disciplines, and update reward systems so that AI-enabled scientific contributions are recognized appropriately.

6.3 For India, Nationally and Globally

For India, the opportunity is historic. Priorities include building shared AI infrastructure such as compute, datasets, and open foundation models beyond elite institutions; creating cross-disciplinary AI-for-science centres; shaping global norms through international networks; developing sector-specific strategies; strengthening AI literacy and reproducibility standards; engaging on biosecurity and dual-use governance; and promoting open datasets, models, and benchmarks for publicly funded research.

The roadmap illustrating the evolution of the field, current landscape, and future directions could be summarised in the enclosed image.

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The Long Arc of AI: Managing Expectations, Maximising Impact

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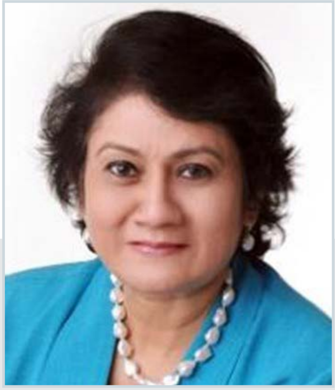

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Artificial Intelligence: Between Hype and Hope

Artificial Intelligence has been categorized by many as a General Purpose Technology with impact on society – akin to electricity, steam engine, or in modern times, the Internet – of immense scale, scope and speed. Yet, as with many transformative technologies before it, expectations from AI are caught in a familiar paradox: we tend to overestimate its impact in the short-term, while underestimating it's long-term consequences.

This duality is important to acknowledge. While many capabilities of AI today appear magical – and hence the hype – a deeper examination reveals that we are still in the early stages of development, understanding and harnessing this technology. The real hope from AI is not just about what it can do today, but how it will reshape systems of knowledge, work, innovation and impact over time.

The Reality Check: Powerful Today, Yet Challenges Remain

Modern AI shows powerful capabilities of synthesizing language, processing multi-modal data such as video or voice, generating insights, and reasoning. Recent frontier reasoning models from OpenAI, Anthropic, Google, Meta and DeepSeek have demonstrated substantially improved mathematical and scientific reasoning, coding and planning, illustrating how rapidly AI capabilities continue to evolve.

Another important development has been the emergence of agentic AI[i,ii]—systems that can not only generate responses, but also plan, use external tools, retrieve information, write and execute code, and carry out multi-step workflows with limited human intervention. These capabilities significantly extend what Al can accomplish in practical settings, moving from passive assistants to active collaborators.

And yet, today's AI is best characterized as possessing "jagged intelligence"[iii] – excellence beyond human levels at certain tasks, yet failure at seemingly simple ones. It can identify patterns in vast datasets yet lacks a grounded understanding of the world those patterns represent. Agentic AI systems remain far from autonomous intelligence: they continue to require human oversight, are susceptible to errors and hallucinations, and often struggle with open-ended reasoning, judgment, and adaptation to unfamiliar real-world situations.

This raises an important distinction: AI systems today do not "understand" in the way humans do. They are systems of statistical pattern recognition and reasoning at scale, but do not possess comprehension rooted in experience or context. As a result, despite impressive advances on reasoning benchmarks such as MMLU, GPQA and SWE-bench, gaps remain in robust grounded common-sense reasoning.

There are also practical constraints to consider: development and deployment of AI is notoriously inefficient in its demands on computation, data and energy. Today's frontier AI models may require millions of GPU-hours for training and consume megawatt-scale power during development. Contrast that with the human brain which operates continuously on roughly 20 watts, while learning throughout life from comparatively few examples, generalizes robustly across contexts, and balances long-term and short-term memory in ways that we still don't fully understand.

And finally, AI systems today have no intrinsic sense of intent, morality or responsibility. Humans, on the other hand, have an intrinsic conscience and intuition for ethics that guide the behaviour of even a 5-year old.

This suggests that AI is not a linear progression towards human-like intelligence, but a fundamentally different paradigm. History cautions against judging AI solely by its current capabilities or limitations. Sutton's "Bitter Lesson"[iv] observes that over decades of AI research, general methods that effectively leverage increasing computation have repeatedly outperformed systems built around handcrafted domain knowledge. Therefore, today's shortcomings in AI should be viewed as points along a trajectory rather than fixed ceilings.

Recognising this distinction between AI's powerful capabilities today, challenges that are continually getting addressed and future expected breakthroughs in AI may help us shape our systems of knowledge, work, innovation and impact for the long arc of AI.

India's Opportunity: From Artificial to Augmented Intelligence

Even as AI's capabilities continue to evolve, India has an opportunity to harness AI's power to complement rather than replace human intelligence, shifting the focus from automation to augmentation. For a country like India, "*Augmented Intelligence*" is not merely an academic concept; it is strategic, and foundational. India's challenges are characterized by scale, diversity, resource constraints, and uneven access to expertise. AI's role in India - combined with Digital Public Infrastructure - is to amplify human potential[v].

In education, AI can enable personalized learning, adapting content to individual students' context, language and needs, while empowering teachers with insights and tools. In healthcare, it can support frontline workers with diagnostic assistance and decision support across diversity of language and literacy, helping bridge gaps in access to scarce medical expertise, particularly in rural areas. In agriculture, AI-driven advisory systems can help farmers with timely information on weather patterns, soil conditions, and crop management, improving resilience, productivity and prosperity. In India's judicial system, AI can help address case backlogs through intelligent case management, multilingual legal assistance, and faster access to relevant precedents, while preserving judicial independence and human oversight.

The common thread across these domains is not automation, but augmentation. The goal is not to replace teachers, doctors, or farmers, but to empower them - extend their reach, enhance their effectiveness, and enable better outcomes. To realise this vision, AI systems must ensure human-in-the-loop design principles, must be accessible, affordable, and adapted to local contexts, including India's linguistic and cultural diversity.

One of India's unique advantages is its Digital Public Infrastructure (DPI), identity, payments and data layer, with built-in principles of interoperability, scalability and inclusion. Combined with AI, new possibilities for innovation and entrepreneurship open up, whether as educators, healthcare advisors, caregivers, agricultural consultants, or small business operators, who shift from centralized to decentralized networks of contextual capability. The question then is whether India can leverage AI to augment human capacity and capability while substituting routine tasks, thereby creating new forms of livelihood and inclusive economic participation.

AI as a Catalyst for Accelerated Innovation

Beyond augmentation, AI is transforming innovation itself. Problems that were once intractable-e.g. in health, sustainability, even mathematics-appear within pursuit, and are domains of active research. In that sense, AI expands the frontier of innovation.

For centuries, our institutional and intellectual frameworks have favoured specialization, which has also led to silos. Real problems, and indeed Nature, is fundamentally interdisciplinary. Nature does not recognize the disciplinary boundaries that humans have created; biological, physical and social systems are inherently interconnected. Even solving real problems in a domain as human as history requires knowledge across archaeology, genetics, linguistics, geology and more. The human body is not a collection of siloed specialities, but an integrated and holistic system shaped by genetics, lifestyle and environment. Similarly, ecological challenges require a systems thinking approach across disciplines of geography, biodiversity, indigenous cultures, hydrology and more.

AI offers a potentially transformative shift - from reductionist to systems thinking. AI's ability to process large, diverse datasets allows it to identify patterns that span traditional boundaries, bridging domains, and enabling new paradigms for problem - solving. By integrating information across disciplines, AI can increasingly support *systems thinking*, although robust multi-domain reasoning remains an active research challenge.

The emerging field of *AI for Science*[vi] demonstrates AI's potential to accelerate discovery by generating hypotheses, simulating complex systems, and exploring vast solution spaces far more efficiently than traditional approaches. Landmark advances such as *AlphaFold*[vii] in life sciences and drug discovery, *GraphCast*[viii] in climate resilience and disaster preparedness, and *GNoME*[ix] in advanced materials for energy and manufacturing illustrate how AI is reshaping the scientific process itself[x]. As India invests in research and expands its scientific ecosystem through ANRF, AI offers an opportunity to accelerate discovery while enabling more researchers to participate in frontier science.

Beyond the digital realm, the emerging field of *Physical AI*[xi] extends intelligence into the physical world through robots, autonomous vehicles, drones, and embodied systems that can perceive, reason, plan, and act in dynamic environments. Powered increasingly by *world models*[xii] that allow machines to build internal representations of their environment, predict the consequences of their actions, and plan before acting, Physical AI represents the next step in AI's evolution—from understanding information to interacting intelligently with the physical world[xiii, xiv, xv]. Such systems can operate in environments that are unsafe or inaccessible to humans, from disaster zones to deep-sea exploration. They can also augment human capabilities in precision tasks, such as surgery or advanced manufacturing.

For India, Physical AI holds particular promise in addressing challenges of uneven access to expertise, labour productivity, and safety, whether through agricultural robotics, autonomous inspection of critical infrastructure, or robots operating in hazardous environments such as mines. As these systems become more capable, however, their safe and trustworthy deployment will depend not only on advances in AI models, but also on robust sensing, control systems, human-machine collaboration, and engineering assurance. To capture this potential, India needs to invest in infrastructure, data, talent and research ecosystems[xvi].

As AI systems move from experimentation to becoming foundational infrastructure—augmenting intelligence, accelerating scientific discovery, and increasingly interacting with the physical world—the nature of the challenge changes. The question is no longer only what AI can do, but how societies build the institutions, infrastructure, and governance needed to ensure that its benefits are widely shared, responsibly deployed, and aligned with public interest.

Trust, Sovereignty and Public Infrastructure

Trust is not a feature that can be retrofitted; it must be built into AI systems through transparency, safety, fairness, accountability, and continuous evaluation. Frontier AI systems present serious risks of hallucinations, deepfakes, jailbreaks and cybersecurity. As AI increasingly influences decisions across healthcare, finance, education, and governance, trust becomes essential not only for adoption, but for legitimacy[xvii, xviii, xix].

Trust, however, cannot be separated from sovereignty. In the AI era, sovereignty extends beyond geopolitical considerations to encompass three interdependent dimensions: *data sovereignty*, ensuring that data reflecting a nation's people, institutions, and economy is governed responsibly; *compute sovereignty*, providing access to the computational infrastructure required to develop and deploy advanced AI; and *model sovereignty*, enabling the development of AI systems that reflect local languages, knowledge, values, and priorities. Together, these determine not merely who uses AI, but who shapes it.

Just as roads, electricity, and the Internet became foundational enablers of economic growth, the next phase of AI will increasingly rely on trusted digital public infrastructure, robust governance, and sovereign capabilities that enable broad-based participation in the AI economy.

For India, initiatives such as the IndiaAI Mission[xx], the AIKosh[xxi] national datasets platform, and BHASHINI's[xxii] multilingual AI ecosystem represent important steps towards building sovereign capabilities. Together, they seek to democratize access to compute and high-quality datasets, foster innovation in Indic language AI, and strengthen an open, inclusive AI ecosystem. Sovereignty is not about technological self-sufficiency in isolation, but about ensuring that nations can participate meaningfully in the global AI ecosystem while preserving agency, resilience, and public trust.

The Long Arc: Inclusion, Innovation, Impact

If we return to the familiar paradox that frames AI—our tendency to overestimate the short-term and underestimate the long-term—then the true significance of this moment lies not just in immediate breakthroughs, but in the trajectory we are setting for the decades ahead. In the short term, AI will continue to surprise us with improvements in productivity, new applications across sectors, and rapid cycles of innovation. These advances will shape perception, often reinforcing both hype and anxiety. But the long arc of AI will be defined by how deliberately we shape its diffusion across society.

Inclusion, therefore, becomes a first-order design principle. The measure of progress is not how advanced AI systems become in isolation, but how widely their benefits are distributed—across languages, geographies, and socio-economic strata.

Similarly, innovation must be understood as cumulative and systemic. The most profound impact of AI will not come from singular breakthroughs, but from sustained investments in research, talent, data ecosystems, and digital infrastructure that allow innovation to compound over time.

Finally, impact must be evaluated over long horizons, while being intentional about AI adoption for augmentation of capacity and capability today. The success of AI will not be measured solely by technical benchmarks or near-term economic gains, but by its contribution to human well-being, societal resilience, and sustainable development.

History suggests that general-purpose technologies create value only when societies redesign institutions, education, business models and governance around them. AI will be no different. The greatest transformation may come not from the algorithms themselves, but from our willingness to rethink how we learn, work, innovate and collaborate. The choices made today will determine whether the long arc of AI bends toward greater inclusion, innovation and societal progress.

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Can Artificial Intelligence Outperform Human Intelligence? – A Historical Perspective

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Abstract

Since the inception of artificial intelligence (AI), significant efforts and breakthroughs are being made to mimic and challenge human intelligence. Historically, one of the major success stories of AI came from mastering the art of playing strategic games and outperforming humans. In one hand, the functional rules of the game are simple enough to learn by the game-playing agents, but achieving professional level performance involves understanding the intricate decision-making abilities against intelligent and unforeseen opponent (sometimes expert humans). With the evolving computational landscape, gradual dominance of AI is witnessed through complicated game-playing agents where AI envisions super-human level intelligence by outplaying the intelligent experts.

Introduction: Can Machines Think?

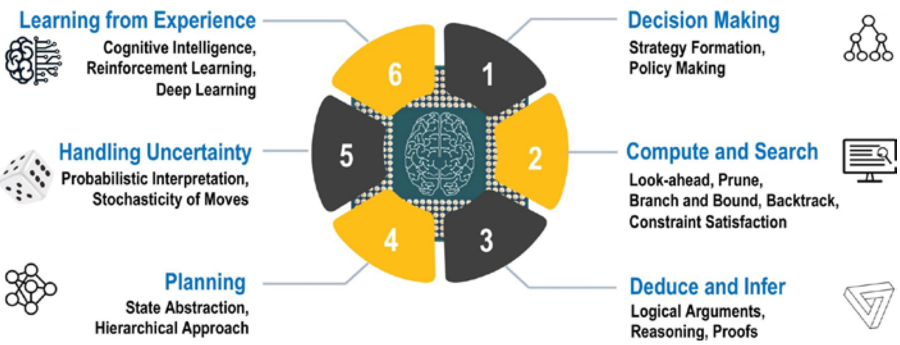
It all started with Alan Turing in 1950, when he asked a pioneering question, "can machines think?", in one of his seminal papers [1]. Arguably, he hinted for a fundamental and rigorous exploration of two important notions – (a) "machine" to characterize 'computation' and (b) "think" to characterize 'intelligence' – which he envisioned in the same paper as an "imitation game". With that question, the genesis of artificial (machine) and intelligence (thinking) became so imperative and penetrating that gradually it not only got expanded through the computational science, but also became an intruder in every other scientific discipline.

The Imitation Game: From Human Cognition to AI

Defining artificial intelligence must start by understanding and imitating the capabilities of human cognition. Studies from neuroscience [2] have broadly reflected the fact that the left part of human brain is primarily responsible for activities like computation, sequencing, mathematical and logical analysis, understanding languages and facts, words of songs, etc.; whereas the right part of the brain primarily governs creativity, imagination, holistic thinking, intuition, arts (motor-skill), rhythm (beats), visualization, tune of songs, daydreaming, etc. Interestingly, modern AI emerges as a convergence of both – the left-brain enabling classical or symbolic methods and the right-brain enabling statistical or learning methods [3].

Why Study Games? Drosophila for AI

Games offer simple rules and deep concepts, that are historically being studied often as a



meaningful test of intelligence and microcosms for real-world setup. The complicacy in decision making, formation of evolutionary strategies, handling uncertainty and adversary – all these make games fun and ultimate testbed to prove general intelligence [4].

[1940 – 1960] Mathematical Foundations: Game-Theory

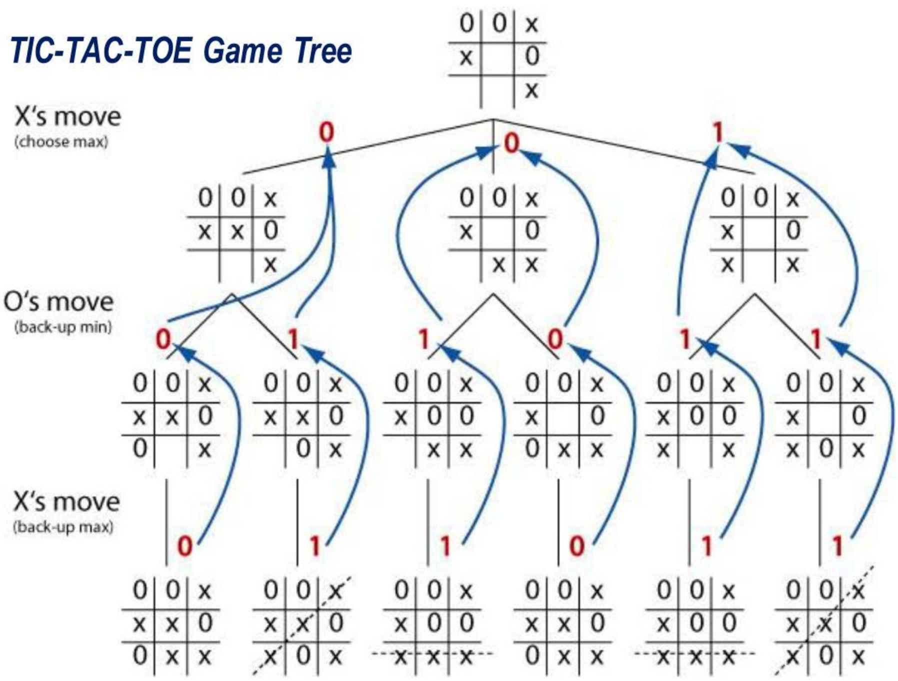
As mathematical and logical foundations are older than that of its computational realization, the optimal strategy behind the game-play has long been formulated through game-theory [5]. In the simplest form, we find two-player games being played alternatively in a round-robin fashion, often leading to zero-sum objectives at the end, meaning that the winning reward is exactly the numerical reciprocal to losing penalty. The solution lies as an optimal strategy that enjoys the best response, $\pi^i_\star$, for *i*-th player if all other players fix their strategies, π^{-i}, which can be formulated as, $\pi^i_\star = \text{argmax}(\pi^i)\ \text{val}(\pi^i, \pi^{-i})$. This optimal strategy thereby forms a Nash equilibrium [6] that becomes a joint policy such that every player's policy is a best response, that is, no player would choose to deviate from Nash which mathematically implies that for any policy response pair $< \pi^i, \pi^{-i} >$, $\text{val}(\pi^i, \pi^{-i}_\star) \le \text{val}(\pi^i_\star, \pi^{-i}_\star) \le \text{val}(\pi^i_\star, \pi^{-i})$.

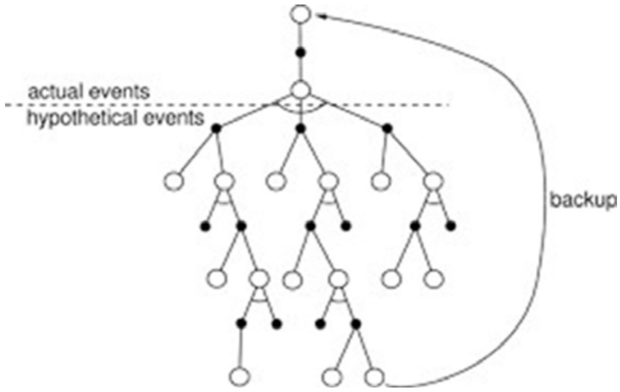
The primary objective of computational methods [7] is to find such Nash equilibria in games, which may be obtained by, (a) classical techniques like game-tree search (involving search, planning, minimax, alpha-beta pruning) [8], or (b) statistical methods like reinforcement learning (RL) (involving Q-learning, deep Q-networks, value/policy iteration/approximation) [9]. Moreover, it is imperative to further generalize this across game formats – ranging from fully observed perfect information Markov games (like Tic-Tac-Toe, Chess, Checkers, Othello, Backgammon, Go etc.) to partially observed imperfect games (like Scrabble, Poker, Bridge etc.) having enormous number of possible board configurations (for example, Go has 10^{170} states [10]) – in order to plan, navigate and operate under (possibly) multi-player cooperative, competitive, adversarial or malicious setups.

[1950 – 1980] Computation became Free: Cognition Era

The era from 1950 to 1980 witnessed a significant growth in computing power while reducing the cost – courtesy to the disruptive technological advances – gradually yielding 'computation to become free'. With such a power, the basic manifestation of intelligence in machines embarked upon imitating the computing capability of humans by look-ahead search and decision-making. Accordingly, Claude E. Shannon (1950) initiated the thinking capacity of machines by producing a hand-crafted fairly strong chess program only through strategic search based on positional value [11].

Later in 1952, Samuel built a checker program with IBM701 machine [12], in which the program kept on improving itself by playing more games within, eventually beating the creator –





the first sign of super-intelligence gathered from experience just like humans learn! With that, the cognitive intelligence seemed realizable inside computing parlance.

[1970 – 2000] Storage/Knowledge became Free: AI Era

The second significant technological advance happened in the era from 1970 to 2000, when

the size of memory or storage devices kept on increasing while keeping its price under feasible limits. This added human-like memory to the machines and also in abundance which further aided in deep computations as some decisions can be immediately taken based on a prior knowledge, thereby saving a lot of computing steps required. Accordingly, problem solving through efficient search, smart storage and quick retrieval (lookup) became the proxy for intelligence, albeit artificial. Significant breakthroughs in game playing came in with it, the most prolific incident being IBM Deep Blue chess engine [13] comprehensively beating Gary Kasparov, the reigning world champion and one of the best players of all times, in 1997 by a margin of 4-2. Interestingly, Deep Blue used high performance parallel alpha-beta search in 480 special-purpose VLSI chess processors where it is capable of searching 200M positions/second with a lookahead 16-40 moves along with 70,000 saved games (with endgames lookahead). The 8000 handcrafted chess features were used to denote positional and piece value information with binary-linear combinations of weights hand-tuned largely by human experts. Similar dominance was also found in Chinook program developed by Jonathan Schaeffer which outplayed checker champion Marion Tinsley (2-0) in 1994 world championship. Later, with the overwhelming advancements in AI, Chinook eventually 'solved' checkers in 2007 [14], implying that it can perfectly play against God!

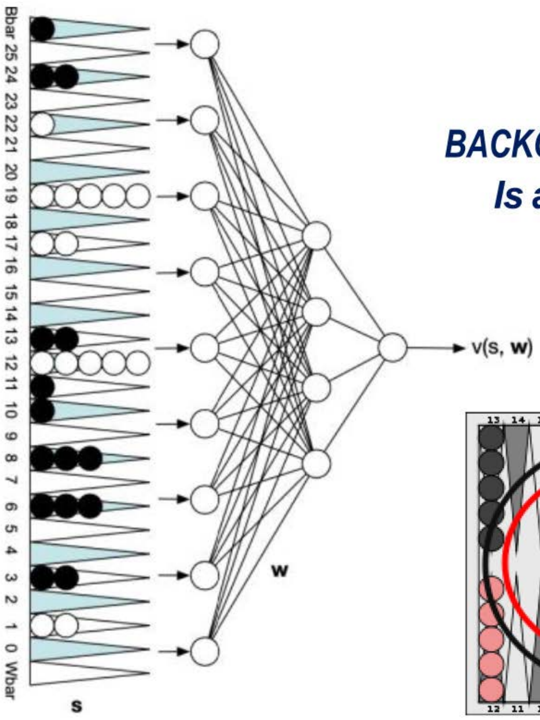
[1990 – 2010] Communication became Free: ML Era

In 1991, a revolution happened, the 'Internet' emerged.

[15]. With that, a world of useful information – that may not be computed, foreseen or required to be stored – also became readily available through search and lookup, aiding into sophisticated decision making. Subsequently, the areas like machine learning (ML) with access to big data and natural language processing (NLP) started to shape up parallelly making communications cheaper and the access to world information free. As a result, IBM Watson started dominating quiz-shows like Jeopardy [16] and emerged as champion emphatically beating reigning quiz-master Ken Jennings (known to be the highest money winner ever in the history of American game/quiz shows). ML kept on challenging humans in games like Minecraft [17] where it discovered treasures by watching only 10 mins of demo-play that matched the exploration of regular child players. With neural network slowly claiming broader applicability through its convolution (vision modeling) and recurrent (sequence modeling) formats, machine could strategize and play games like PingPong (table-tennis) better.

Advanced techniques, like temporal difference learning through self-play training and lookahead search applied over

deep neural networks, produced an astonishingly capable program, named TD-gammon by Gerald Tesauro at IBM Research, which become the world Backgammon champion [18] defeating Luigi



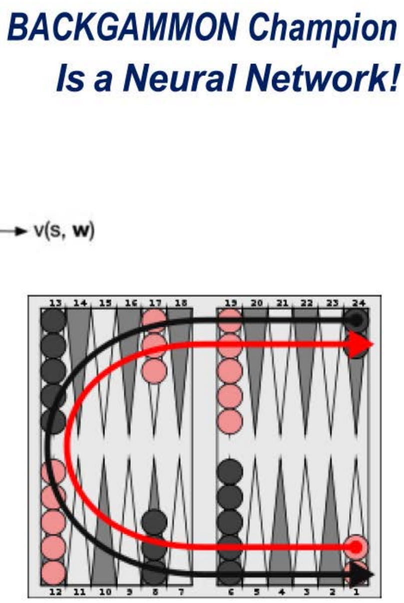
Villa (7-1) in 1992. Starting from a strong intermediate level even with zero expert knowledge, TD-gammon reached to an advanced level (1991) just by hand-crafted embedded features, then to a strong master level (1993) with 2-depth search and finally to the superhuman level (1998) with 3-depth search.

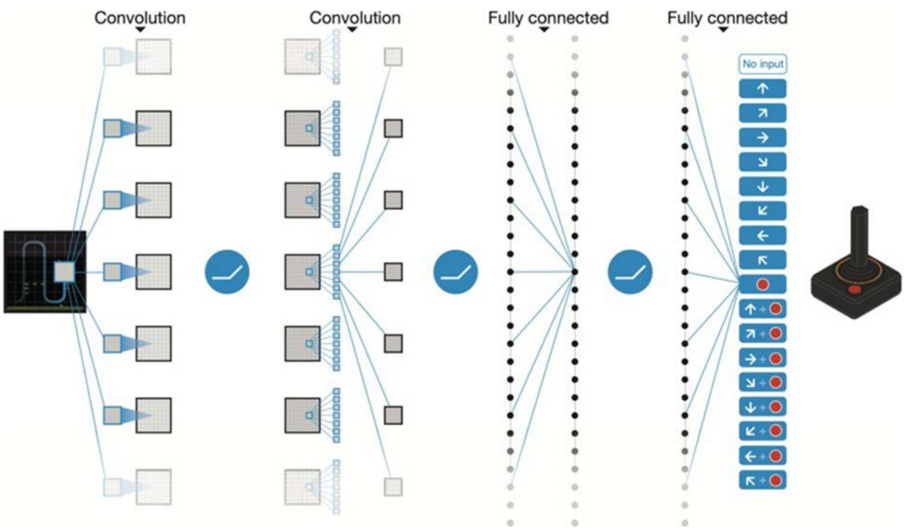
[2000 – 2020] Intelligence became Free: DL & RL Era

The unprecedented growth and proven success of AI kept making steady inroads into various sectors where human never thought of being dominated, catapulted by deep reinforcement learning (RL) which mimicked human-like reward-oriented sequential decision making involving self-play and techniques [5] such as Monte -Carlo (MC) and Temporal Difference (TD) learning. One of the prominent successes came through using Deep Q-Networks (DQN) gaining human-level expert controls in video games like Atari [19].

MC methods and minmax search combined with RL became effective in games like Othello where Logistello [20] defeated world champion Takashi Murukami (6-0), and Scrabble where Maven [21] beat world champion Adam Logan (9-5) with an astounding low error rate of just -3 points per game. Further, TD methods prove their efficacy in games like Checker (Samuel's program using TD-Root) and Chess (KnightCap using TD-Leaf and Meep using Tree-Strap beating 13/15 international chess masters). Classical AI techniques received higher traction with RL involving simulation-based MC search. All AI methods available in agent's repertoire made us believe that true intelligence is accessible inadvertently or freely.

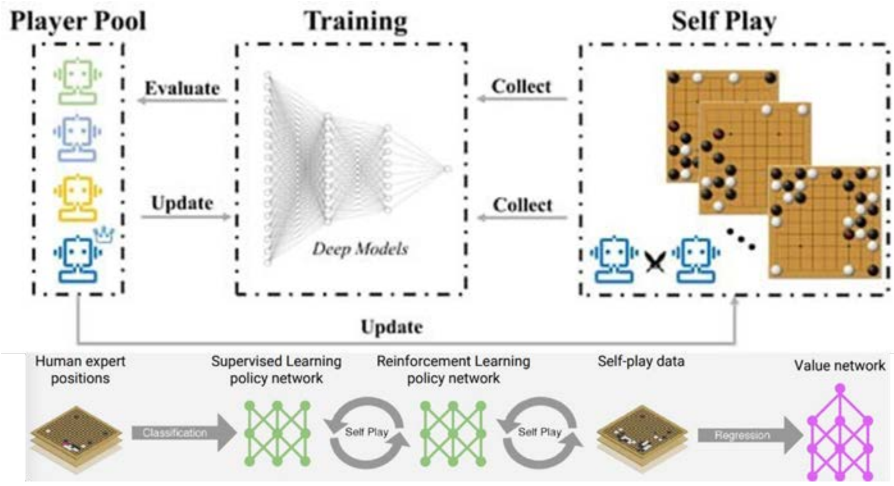
The ultimate grand challenge for AI was to achieve dominance in the ancient game of Go which remained brutal for traditional game-tree search due to enormous number (10^{170}) of board configurations. The successful

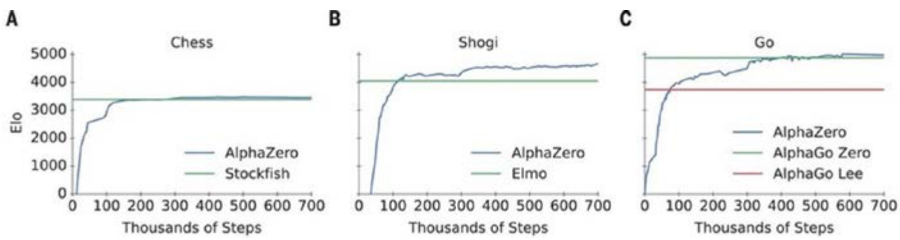


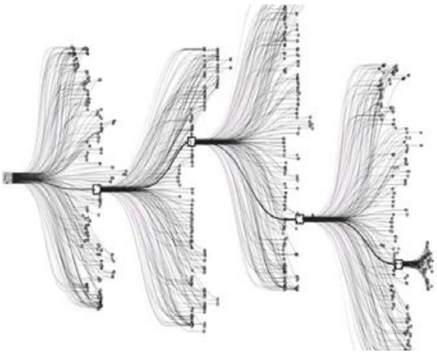


Deep Q-Network for ATARI Games

strategies originated from the policy and value networks combined with deep RL, trained using self-play and simulation-based Monte-Carlo Tree Search (MCTS) from 30M human expert game positions, made AlphaGo [22] emerge convincingly as the Go champion defeating Lee Sedol, arguably one of the best Go players of all time, by a 4-1 margin in 2016.







GO Game Tree (Partial)

[2015 – Onwards] Imagination became Free: VR Era

With the emergence of generative and imaginative AI techniques, courtesy to Generative Adversarial Networks (GAN), Variational Autoencoders (VAE) and Transformers (attention-driven deep networks), creating new knowledge seemed feasible commencing the glorified era of virtual reality (VR). The prompt-based large language models, like ChatGPT, Gemini. Claude, CoPilot, etc. appears to be magically imaginative and intelligent upon querying any need and getting answers for free. A pivotal step in game-play was also initiated when AlphaZero [23] started mastering games without human intervention and knowledge – all by itself through self-play from scratch – taking only 4 hours to surpass Stockfish (for Chess), only 2 hours to surpass Elmo (for Shogi) and only 8 hours to surpass its own AlphaGo version (that defeated Lee Sedol).

In 2020, MuZero [24] achieved an expert-level rating for any game without knowing game rules or underlying dynamics, just by observing expert game-play and learning the strategies. In games where there is partial and imperfect information, RL started dominating by its imaginative and generative super-power, as in SmooCT (for Poker) outperforming massively forward searching agents and then capitalizing it in Cepheus (for Poker) attaining the 'perfect'

Program	Level of Play	Program to Achieve
Checkers	Perfect	Chinook [14]
Chess	International Master Superhuman	KnightCap [27] / Meep [28] DeepBlue [13]
Othello	Superhuman	Logistello [20]
Go	Grandmaster Superhuman	MoGo / CrazyStone / Zen [29] AlphaGo [22]
Backgammon	Superhuman	TD-Gammon [18]
Scrabble	Superhuman	Maven [21]
Poker (Multi-Player)	Superhuman Perfect > Human	SmooCT, Polaris [30] Cepheus [25] (Pluribus) [31]
Atari	> Human	Deep Q-Net (DQN) [19]
StarCraft	> Human	AlphaStar [26]

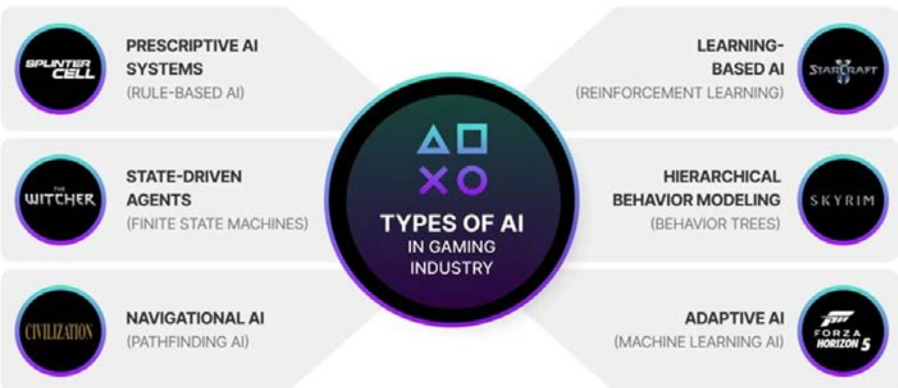
game-play (against God) [25]. Later, AlphaStar (2019) [26] uses multi-agent RL with human-like imitation learning and imaginative self-play to achieve superhuman level performance in StarCraft II.

Conclusion and Summary: Achievements & Dominance

Through the coveted pavement inaugurated by AI and later decorated by ML, DL and RL, expert-level game-play automation has travelled a long way. Aligning with such historical progress, strategic board games are also being dominated by expert AI/ML programs. The level of play achieved by the first of such programs is presented below.

The primary driver for expert game-play can be attributed broadly from six capabilities from AI: (a) ability to make decisions by strategy formation, (b) ability to compute and search using look-ahead, backtrack, branch and bound and constraint satisfaction, (c) ability to deduce and infer by logical reasoning and proofs, (d) ability to plan by hierarchical and state abstraction, (e) ability to handle uncertainty using probabilistic interpretation and move stochasticity, (f) ability to learn from experience through training using ML/DL/RL framing

Program	Input Features	Value Function	RL Method	Training Process	Search Technique
Checkers (Chinook)	Binary, Pieces, Pawns…	Linear	TD Leaf	Self-Play	αβ Pruning
Chess (KnightCap / Meep)	Binary Pieces…	Linear	TD Leaf / TreeStrap	Self-Play/ Expert	αβ Pruning
Othello (Logistello)	Binary Disc Configs	Linear	MC	Self-Play	αβ Pruning
Go (MoGo / AlphaGo)	Binary Stone Patterns	Linear/ Neural Network	TD	Self-Play/ Expert	MCTS
Backgammon (TDGammon)	Binary Num Checkers	Neural Network	TD (λ)	Self-Play	αβ Pruning / MC Search
Scrabble (Maven)	Binary Rack letters	Linear	MC	Self-Play	–
Poker (SmooCT)	Binary Card abstract	Linear	MCTS	Self-Play	MC Search
Atari (DQN)	Binary Image pixel	Neural Network	Experience Replay	Self-Play	–
StarCraft (AlphaStar)	Binary Image configs	Neural Network	TD (λ)	Self-Play	MC Search



Source: https://markovate.com/blog/ai-in-gaming/

cognitive intelligence. Most strategic game-playing programs of today have outperformed expert professional players through self-play and experienced training added with the simulation-based search and pruning. The successful recipes for the champion programs are highlighted below.

With the prowess of AI, gaming industries are completely getting revamped. Various approaches from AI and RL are particularly being used in professional development and game-play for widely adopted games, as illustrated below.

Future: Is the Game Over? What's Next?

In complex multi-player games, humans often negotiate to collaborate with some as well as compete with others with strategic reasoning and conversational negotiation using NLP (typical share-market situation can be thought of as a practical example). This involves diplomatic transactions considering behavioral aspects for cooperation. Diplomacy in expert game-play is a challenge, which was also proposed by Meta AI, in a game named CICERO [32], where the objective is build cooperative and hybrid AI engines capable of handling diplomacy through complex strategies. True breakthrough for AI should include understanding and imitating social, behavioral, economic and political aspects into the diplomatic collaborations to build human-like negotiators for ultimate decision making.

The future roadmap of AI driven strategic gameplay focuses on transitioning from perfect-information board games to complex, multi-agent, and hidden-information environments. Key development areas include generative world models, hierarchical multi-agent coordination, and agentic large language model (LLM) reasoning. With wider adoption and high reliance on emerging AI models in sophisticated decision making, a crucial challenge surfaces in understanding the gameplay behaviors as performed by self-learning agents. Hence, it will become imperative to explain the steps in which the decisions are being made in game-play. There is a clear tradeoff between the complicated AI strategies learned and its human-understandable interpretation – more is the complexity of a learned model; less becomes the capability of reasoning the rationale behind its decisions – thereby creating a void in human controllability of these agents. This would not only make the machines to become more dominant, but also will prevent humans to learn from them and adapt accordingly.

Finally, in one hand, all these rapid developments may gradually align AI to come closer to human enactment; however, one the other hand, human may get further away to remain and make decisions humanly due to their interaction with machines and AI driven smart agents.

Let us see how humans as well as AI unfolds and adapts themselves to co-exist in future...

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Anthropomorphism in AI: Past, Present, Future

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Abstract

Among the most overpowering features of AI today, besides the technology itself, is its widespread perception of AI as being human-like. Today's public discourse abounds with narratives that interleave AI with human traits like consciousness, creativity and skills. In this brief article, we will journey into the contours of the phenomenon of anthropomorphism - the attribution of human-like attributes - to AI. Drawing upon the dominant vectors of anthropomorphism in AI across historical and contemporary times, we will briefly conclude by considering the likely shades of anthropomorphism in the future.

Introduction

When we search for images of Artificial Intelligence (AI) on the Web, we are inevitably flooded with images of humanoid robots. These make their way to adorn magazine articles on AI, and other cultural imaginations of AI. However, we may never have come across an AI in the form of a humanoid-robot, of course, they may exist, but only on the fringes of the technological universe. In this article, we historicize the pervasive attribution of human traits to AI technologies, a phenomenon that is known as anthropomorphism. More generally, anthropomorphism is the tendency to imbue the real or imagined behaviour of nonhuman agents with humanlike characteristics, motivations, intentions or emotions (Epley, Waitz and Cacioppo, 2007). It has been observed that anthropomorphism is rooted in relationality and interactions (Airenti, 2015) and is a phenomenon that also substantially influences AI scholarship (Salles, Evers & Farisco, 2020).

We first start by looking through the historical origins of anthropomorphism in AI, moving over to the manifestations of the phenomenon in recent and current times, and conclude by briefly looking forward into the possible anthropomorphic AI worlds that may lie in store for us in the future. The discussion will proceed through delineating the progression of anthropomorphism through a series of vectors of the phenomenon, each of which emerges within a historical context and interleave with other vectors in a variety of ways. The dominant vectors that figure in the narrative are outlined in Figure 1; the text in the subsequent sections will refer to these as the article progresses by attempting to unravel AI anthropomorphism through the ages.

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The History

It so happens that the origins of AI are steeped in anthropomorphism, at least, there is a way to look at it so. The Turing Test may be regarded as a test of anthropomorphism, an aspect that is very apparent in the original name Alan Turing used, the 'imitation game' (Turing, 1950).

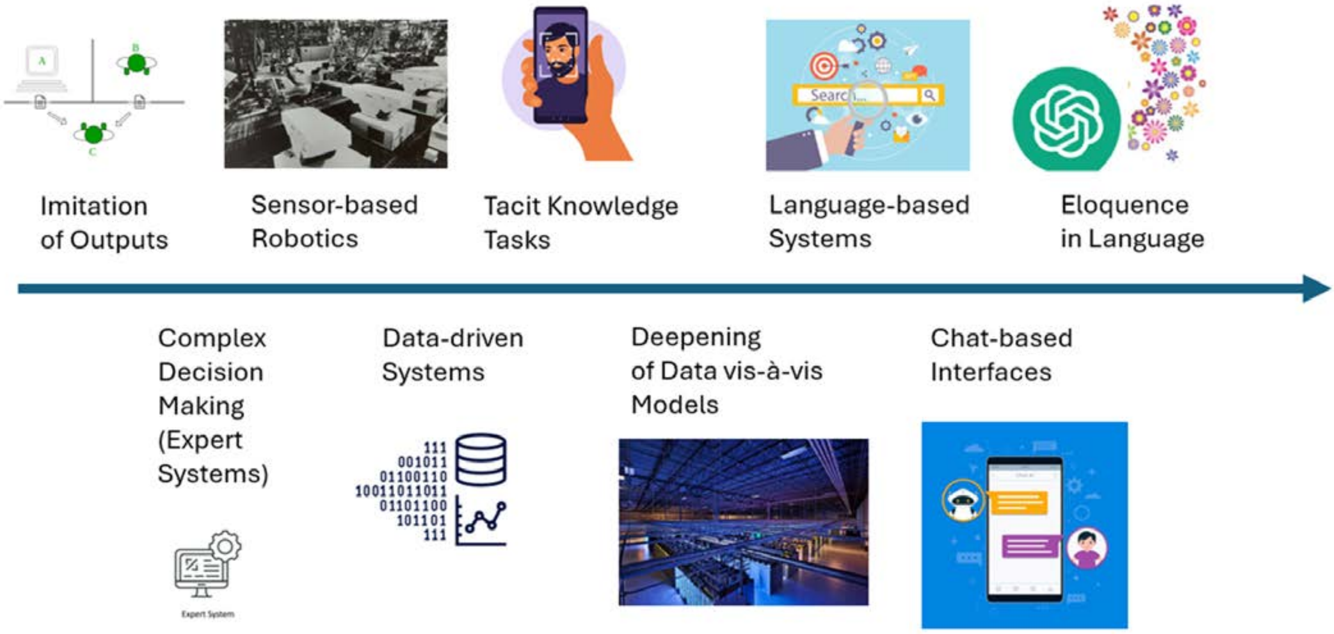

Fig. 1 - Vectors of Anthropomorphism through the Ages. The figure illustrates how anthropomorphism in AI has progressed through a series of vectors over the three-quarters of a century of AI's history. Starting with AI anthropomorphism in the Turing test, through the expert systems and sensor-based systems eras, the contemporary vectors of anthropomorphism in the data-driven era rely largely on human-generated data presented in human-like interfaces. This article outlines the nuances of the development of anthropomorphism in AI through these various vectors across the decades.

The Turing test seeks to identify ways in which a machine can be mistaken for a human, when the judgement is restricted to be made only at the level of output. Much later, John McCarthy, one of the pioneers of AI, would write that 'intelligence is the computational part of the ability to achieve goals in the world'. In contrast to conceptions of human intelligence grounded in thinking processes and anchored in distinctively human facets such as society, history, culture and human experiences, it is to be seen that AI, from its initial days, relies on a reductive conception of intelligence that focuses on computational processes and production of outputs.

The reductive conception of intelligence is often attributed to Turing's genius but is indeed rooted in imaginaries of intelligence that stem from a distinctively Western intellectual backdrop. One can see perspectives of a computational perspective of intelligence shining brightly through centuries of Western philosophical scholarship, as I have argued recently (Deepak P, 2026). These include Rene Descartes, who professed a hierarchical relationship between mind and body, as well as Thomas Hobbes, who was bold enough to characterise intelligence as computation. Indeed, dualisms form a key aspect of the philosophical tradition within Western civilisation (Rintala, 2012). These stand in sharp contrast to the focus on intelligence as a social construct within various strands of Indic literature that emphasise the role of society in human intelligence. Indeed, this could be read in line with the fact that life in societies such as India has always been rooted in collective thinking and decision-making, in contrast to Western societies that are noted for their individualism. These cultural differences are much deeper, as it has been argued(Nass et al, 1994), the Western model of treating the individual as free contrasts with cultures that treat the individual as part of a complex social organism, and these reflect in how different cultures know the world.

While imitation of human outputs is quite abstract and subjective, the conception of the Turing Test model brought it into the realm of objectivity and measurements. Josef Weizenbaum, another AI pioneer and later critic, puts this eloquently in words (Weizenbaum, 1962), 'success can be measured by the percentage of the exposed observers who have been fooled multiplied by the length of time they have failed to catch on'. Thus, it is not just transient imitation that is targeted, instead, AI seeks to achieve durable and consistent imitation. As long as people can confuse the imitation for the original, in other words, as long as anthropomorphism works, AI could be regarded as successful. In fact, Josef Weizenbaum is credited with the discovery of the human capacity for anthropomorphism for he observed that his simple rule-based chat system, called ELIZA, was effective in eliciting emotional responses from users. This would be later called the ELIZA effect, one that Douglas Hofstadter defines as 'susceptibility of people to read far more understanding than is warranted into strings of symbols, especially words, strung together by computers' and characterises as 'ineradicable' (Hofstadter, 1995). Even outside the discipline of AI and broadly in computing, such human vulnerabilities have been noted, for example, the famed 'computers are social actors' paradigm within human-computer interaction notes that 'social responses to computers are commonplace and easy to generate' (Nass et al., 1994).

The three-quarters of a century of AI scholarship from the 1950s could be regarded as an exploration into pathways of realising AI through programmed systems. Among the pathways considered are complex rule-based expert systems such as MYCIN, sensor-based robotics systems in factories, and game-playing systems such as DeepBlue. While these are anthropomorphic in inner workings in that they seek to imitate human behaviour, they are not necessarily anthropomorphic in presentation, it is apparent that an industrial robot is unlikely to be confused for a human.

The arrival of data-driven systems in the 1990s arguably marked a deepening of anthropomorphism in AI, for these seek to expand the realm of AI into human-oriented tasks based on tacit knowledge that do not yield to explicit representation. These include tasks such as identifying faces within images (classification), speech-to-text systems (transcription), and various forms of pattern-based decision-making systems (e.g., automated shortlisting). This marked shift was facilitated by the usage of data as a key aspect of these systems; the decisions became more informed by the data than the programs that work over them. The fundamental idea is simple, to move the decision-making calculus from one of programmed logic to that of the logic of patterns drawn from large datasets. With the data being human generated, the growing influence of data within these AI systems correlates well with a deepening of anthropomorphism.

Contemporary Developments

The late 1990s saw the emergence of a distinctively new form of data-driven technology, that of Web Search. While Web Search cannot be seen as AI proper, it does follow the broader AI framework of arriving at results based on patterns from data. The point of departure is however stark, in contrast to the paradigm of AI working over relational data, the data and the technology were distinctively anchored in natural language. Invocations of the technology involve the usage of keywords, and the inner workings are based on pattern-finding over text data. Language is often understood to be distinctively human, in a very vivid manner, with it being even referred to as 'practical consciousness' (Marx and Engels, 1932). The substantial entry of data-driven technology into the realm of natural language arguably turned up the anthropomorphism in the technology one notch higher.

The 2000s and 2010s marked another shift in the workings of data-driven AI technology. While the 1990s and early 2000s were marked by a phase in AI research where the merit of the technology was largely seen in making bespoke and appropriate modelling choices, the 2010s saw the focus shifting towards data. With large datasets becoming available in plenty, hand-in-hand with the emergence of neural networks which offer highly flexible and non-linear modelling and optimisation choices, AI research papers largely started justifying merit through usage of larger and more appropriate datasets. As an AI researcher, this author had observed, through the late 2010s, the gradual erosion of affinity to theorems, proofs and rigorous argumentation within AI research. In place of such mathematical and verbal instruments, AI research has witnessed a trend towards abundant usage of neural networks presented through architecture diagrams (Marshall, Freitas and Jay, 2025) that are justified post-hoc by the quality of results they generate. In terms of anthropomorphism, this opened up a pathway towards greater usage of human-generated data in building AI systems, further enhancing its potential for anthropomorphic workings. With the operation of complex neural networks being increasingly opaque, it became progressively easier for even programmers to think of AI as having a mind of its own.

The more recent technologies of Generative AI, or large language models, which most people consider simply as AI, are arguably a key phase in contemporary AI. They marked another step in anthropomorphism drawing upon the previous trends of natural language usage and large neural network models, one that is marked by their delivery over natural language chat interfaces. It is to be noted here that chat-based interfaces are not a new phenomenon in AI, the modelling of the Turing Test involved a chat-like interface, and a key AI system from the 1960s, ELIZA, discussed earlier, was delivered over a chat interface. The re-emergence of chat interfaces at a historical point of AI where text processing techniques have developed substantially, however, led to tremendous enthusiasm in claiming successes over the Turing Test. If 'Googling' was a linguistic artefact of the web search era, the lingo of 'asking ChatGPT' in the 2020s is notably much more anthropomorphic.

Armed with a technology such as neural networks that has anthropomorphism potential, and delivered over a chat-based interface, one might be tempted to believe that anthropomorphism within Generative AI could have reached a zenith. Yet, there are structural issues at play, as is the case with any technology, for technologies are fundamentally limited in imitating humans. The data-driven technology of Generative AI has a structural effectiveness gradient, while data-rich spaces offer an easier playground, Generative AI struggles while working in data-sparse spaces. These have a distinct geopolitical gradient too, for data on the Web is largely aligned with the Global North. For example, it is inevitable that questions around tribes in Andaman would draw lower-quality answers than those about scientists in America. The fragility in data-sparse spaces is a recipe for the breakdown of anthropomorphism, for it gives away the machinic calculus underneath. Today, Generative AI technologies have been fortified with two anthropomorphic elements in an apparent attempt to mask such structural issues. First, they are trained in ways that lead them to make up narratives that don't exist, by patching together tangential but textually related content. For example, questions around a 1970s niche Hindi movie for which data is very limited could be answered by falling back to general patterns around 1970s Hindi movies. These have also been adorned with an anthropomorphic term, hallucinations. The pervasive anthropomorphism of AI chatbots isn't without its detractors, an early reference to large language models as 'stochastic parrots' (Bender et al., 2021) has served as an effective antidote to AI anthropomorphism within some parts of AI scholarship. Second, they have been trained in ways to generate pleasing and eloquent content, indeed, AI chatbots have been noted for their sycophancy, politeness and a penchant for repeated apology-making. An emerging literature on user perceptions about LLMs indicates that user interactions with them are ridden with significant expectation mismatches (Gröner and Chiou, 2024). These mark the frictions that anthropomorphism faces in the current era, which may also point to the ways that AI anthropomorphism may shape up in the future.

The Future

While the ways of anthropomorphism in the future may be hard to predict due to obvious reasons such as the volatility of the AI scene in the contemporary world, certain aspects are noteworthy. One way to approach this question would be to probe the structural incentives that have driven anthropomorphism through the various phases of AI. Another would be to juxtapose such incentives against the shortfalls in today's anthropomorphism. It is indeed conceivable that the driving forces for AI anthropomorphism are in the plural. Yet, among the key drivers is that of commercialisation of AI. This is evident when one sees that each epoch of anthropomorphism, whether it be expert systems, sensors, web search or generative AI, has yielded large industries, and resulted in tremendous amounts of commercial activity within AI. Very recent developments suggest that the apparent nexus between the US administration and big tech bosses may be opening a pathway towards aligning the technologies to serve American hegemony. For example, the recent executive order, EO 14409[1], institutes an incentive for big tech companies to pre-release their AI models to the US administration in exchange for a potential classification as a 'covered frontier model', a designation which could help improve global market reach. How these pre-release pressures and designation from the US administration could qualitatively impact AI as a technology and reflect in terms of anthropomorphic flavours, however, remain to be seen. This may be a near-term development that could have long-term consequences. On the contrary, the rapid advancements in AI from regions such as China offer opportunities for Global South regions to counter Western hegemony in the AI space.

With big tech companies vying to tap into markets in the Global South, we might start to see diversified anthropomorphism, where the choice of words and accents are differentiated to enable better appeal to people and cultures in the Global South. Among the most notable aspects of AI-generated content, one that today's AI detection technologies pin their workings on, is that of extremely smooth and polished text. With this being increasingly seen as a point of divergence between human-authored and AI-generated text, it is conceivable that a kind of engineered imperfection may be explored to re-establish the synergy between AI and humans. Indeed, coding imperfections into AI could have a role in fostering anthropomorphism. Today's anthropomorphic AI is delivered through chat-based interfaces and is fundamentally limited in communicative ability, for it cannot encompass fine qualitative aspects of communication, such as body language. It is likely that we may see an increasing focus towards integrating chat-based interfaces with hardware, or the evolution of today's personal digital assistants to encompass more human-like features. Such developments may spark a renewed interest in the development of objective measurements of anthropomorphism (Bartneck et al., 2009), ones that could be expressly aligned with big tech profiteering goals. These all could interplay with the current enthusiasm around agentic AI, where AI is used to work across systems, rather than in a mode of working in silos. While these could be long-term developments, we might start seeing a network of anthropomorphic terminologies (such as 'personal intelligence') in advertising material which could be used by corporations to test the waters for market readiness. The deepening of anthropomorphism isn't necessarily a given. Progressive movements and activist organisations could sway public discourses in ways that enhance awareness of the role of machines vis-à-vis humans. In other words, the library of vectors of anthropomorphism may be supplemented by those that seek to counter anthropomorphism too. Whatever be the ways in which things shape up in the future, one thing appears certain, anthropomorphism would remain an active playing field for developments in AI, at least for the foreseeable future.

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Five Decades of DST–SAIF: Building India's National Backbone for Research Infrastructure

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Abstract

Regional Specialised Dedicated Infrastructure is envisioned as a pivotal driver for advancing scientific progress and strengthening India's scientific capabilities. In a country with a vast geographical expanse and numerous research institutions, it is challenging to support the infrastructure needs of every organisation individually. Establishing regional centres provides a pragmatic solution by addressing the diverse requirements of the scientific community, ensuring accessibility, inclusivity, and collaborative growth. The Department of Science and Technology (DST)'s Sophisticated Analytical Instrumentation Facility (SAIF) scheme has been instrumental in this effort, playing a crucial role in advancing scientific research and technological development in India over the past five decades. At present, there are a total of 15 SAIF Centres spread across India, collectively housing more than 130 high-end sophisticated analytical instruments. This article provides a comprehensive analysis of the SAIF scheme's evolution over the last five decades, focusing on its journey, inventory of advanced instrumentation, and key milestones. Significant achievements include a growing user base, the self-sustainability of laboratories, impactful training initiatives, increased scientific publications, and advancements in intellectual property generation. Additionally, the scheme has fostered global partnerships through various Memoranda of Understanding (MoUs), further enhancing its impact on scientific and technological innovation.

Keywords

Sophisticated Instruments; DST-SAIF; Capacity Building; Research and Development; Research infrastructure

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1. Introduction

Scientific research is fundamental to advancing knowledge, fostering innovation, and addressing emerging technological challenges. A well-established research infrastructure plays a crucial role in supporting scientists, researchers, and students in conducting high-quality investigations that contribute to both scientific progress and societal development. However, for developing nations like India, balancing economic growth with the need for cutting-edge research facilities has been a persistent challenge 1.2 3 Recognizing this, the Ministry of Science and Technology, Government of India (GoI) launched the Sophisticated Analytical Instrumentation Facility (SAIF) scheme in 1974 to provide researchers with access to state-of-the-art analytical instruments. Initially known as Regional Sophisticated Instrumentation Centres (RSIC) and later renamed SAIF in 2002-03, this initiative with its 15 centres across India has democratized access to high-end equipment such as Nuclear Magnetic Resonance (NMR) machines, electron microscopes, and spectrometers, ensuring that scientists/researchers can conduct cutting-edge research irrespective of their institutional affiliations.

The primary objective of SAIF is to enhance research excellence by providing open access to sophisticated instrumentation, enabling researchers to push scientific boundaries and drive technological advancements. Beyond instrument accessibility, SAIF also facilitates preventive maintenance, calibration, and repair to ensure the sustained functionality of research facilities 4. Additionally, through workshops, training programs, and collaborative projects, SAIF strengthens skill development and knowledge dissemination, equipping researchers with the expertise to effectively utilise advanced analytical tools. Furthermore, by fostering strong academia-industry linkages, SAIF enables startups, MSMEs, and industries to leverage high-end research facilities for product development, technology transfer, and R&D, thus accelerating innovation and enhancing India's global competitiveness in science and technology.

SAIF centres play a crucial role in supporting the Government of India's efforts such as the Scientific Research Infrastructure Sharing, Maintenance, and Networks (SRIMAN) Policy[5], the Anusandhan National Research Foundation (ANRF)[6], and the Vigyan Dhara Scheme. These programs are designed to enhance scientific research capabilities, encourage interdisciplinary collaboration, and align with the goals of India's National Education Policy (NEP) 2020. Additionally, SAIF centres and these initiatives significantly contribute to achieving key United Nations Sustainable Development Goals (SDGs), including Quality Education (SDG 4), Industry, Innovation & Infrastructure (SDG 9), Climate Action (SDG 13), and Good Health & Well-being (SDG 3). As SAIF celebrates five decades of operation, its impact on India's scientific advancement and technological innovation is clear, ensuring that research achievements lead to tangible socio-economic benefits for both the nation and the world. Fig. 1 shows the distribution of SAIF centres across the country.

2. Inventory of Instruments Available at SAIF Centres and Methods to Reach

and has research experience at the National Institute of Oceanography (NIO), CSIR. His research has focused on coastal and estuarine dynamics, particularly tide–river runoff interactions, tidal propagation, estuarine stratification and salinity variations. He has expertise in oceanographic data analysis, coastal modelling, remote sensing and GIS. At DST, he contributes to programmes and initiatives aimed at strengthening research infrastructure and scientific capabilities in universities and higher educational institutions across India.

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Stakeholders

The SAIF centres are outfitted with advanced analytical

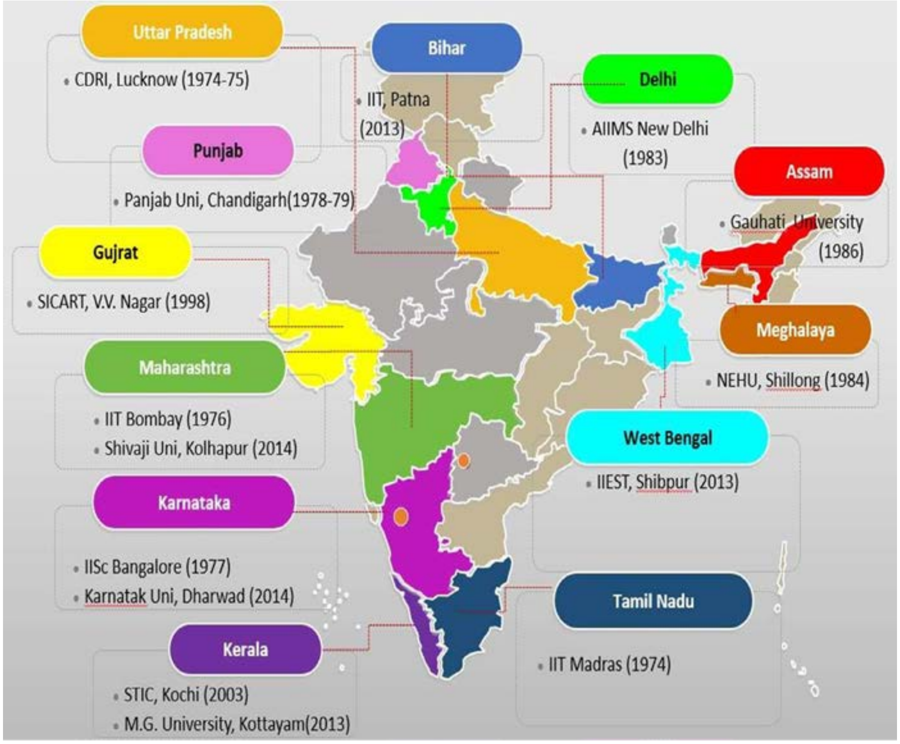

Fig. 1 - Pan-India spread of the DST–SAIF centres across major scientific institutions.

Fig. 2 - Major facilities created through the SAIF program at different centres.

equipment designed to support research across various fields of science and technology. Researchers from academic institutions, industrial R&D, MSMEs, start-ups, and other industries can access these facilities for a nominal fee. At 15 SAIF centres, an inventory of more than 130 sophisticated instruments is available. A collage of major facilities created through the SAIF program may be seen in Fig. 2.

It includes various advanced electron microscopes, spectroscopic techniques, chromatography techniques, thermal analysis systems, etc. A comprehensive inventory of instruments is available at various SAIF centres across India, each equipped with advanced analytical tools to support diverse research needs. For example, SAIF centres at Panjab University[8], IIT Madras[9], and IIT Bombay[10] offer a wide range of instruments, including thermal analysis systems, electron microscopes, X-ray crystallographic, electron spin resonance spectrometers, various spectroscopy and chromatography techniques. Some SAIF centres, such as IISc Bangalore[11] and AIIMS Delhi[12], provide specialised equipment for advanced nuclear magnetic resonance and electron microscopy techniques, respectively. Additional notable facilities are available at other SAIF centres featuring extensive arrays of spectrometers and chromatographs. Each centre offers contact information and dedicated websites for further inquiries, and all SAIF instruments are registered on the I-STEM portal, ensuring that researchers can easily access the resources they need.

3. Five Decades of Research Infrastructure Support: Unpacking the Transformative Impact of the DST-SAIF Scheme on India's Scientific Progress - Data Analysis for Deeper Insights

The Department of Science and Technology (DST), Government of India, launched the Sophisticated Analytical Instrumentation Facility (SAIF) scheme in 1974 with the vision of providing shared access to high-end analytical instruments to the scientific community. Over the past five decades, the scheme has evolved into a cornerstone of India's research ecosystem. Considering the breadth of the SAIF Programme's 50-year journey, this article presents a focused analysis of the most recent

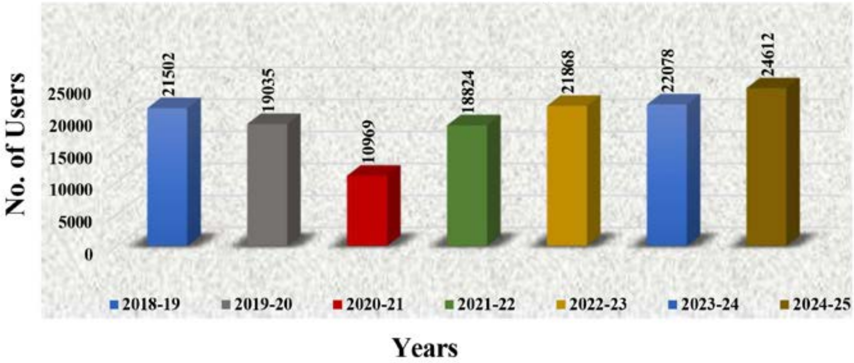

Fig. 3 - Total number of users of SAIF centre in each year

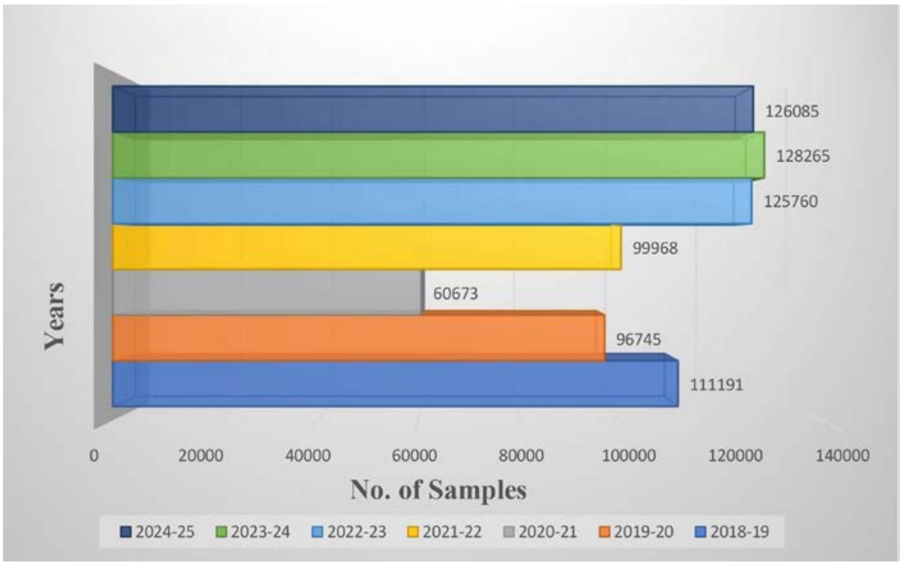

Fig. 4 - Total number of samples analyzed by SAIF centres in each year.

seven years, offering a representative cross-section of the scheme's evolution and the impact of the COVID-19 pandemic on facility operations and user demand. The article highlights the transformative contributions and achievements of the DST-SAIF scheme during this period, with emphasis on its support to academia, industry, health sectors, and national innovation.

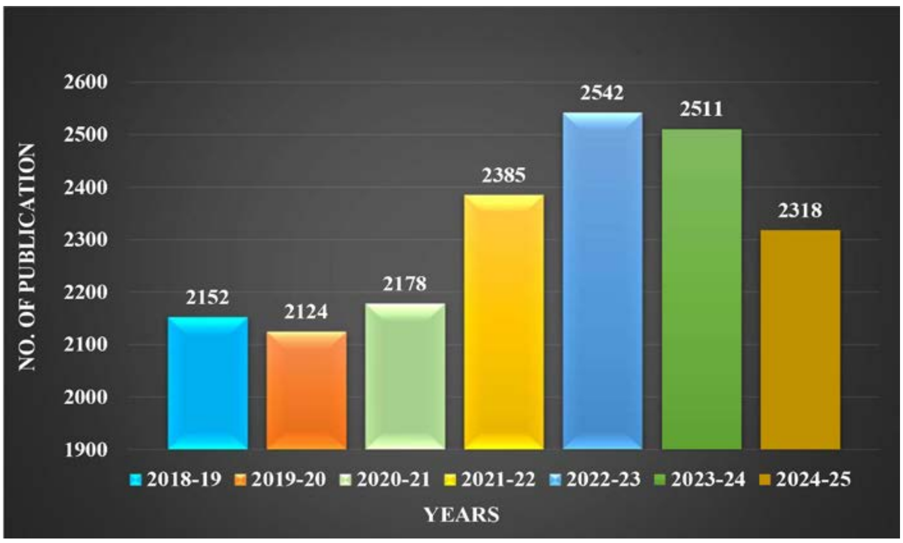

Fig. 5 - Total number of publications reported by SAIF centres each year.

One of the most significant indicators of the scheme's success is its expansive and diverse user base (Fig. 3). From 2018 to 2025, SAIF centres served a total of 1,33,498 users across academia, research institutions, industry, and government bodies. The number of users showed resilience during the pandemic years, dropping to 10,969 in 2020-21 but rebounding to 24,612 by 2024-25. These figures underscore SAIF's indispensable role in maintaining scientific momentum even during national emergencies. The facilities have been instrumental in providing critical infrastructure for high-quality research in chemistry, physics, materials science, nanotechnology, pharmaceuticals, environmental science, and more.

SAIF centres analysed a total of 7,48,687 samples during these seven years (Fig. 4). Sample analysis ranged from metals and polymers to biological and geological materials. The diversity and volume of samples highlight the multi-disciplinary application and relevance of SAIF instruments. Notably, despite pandemic-induced disruptions, SAIF centres rapidly resumed services and experienced a surge in analytical demands in the post-COVID period, reaching 1,26,085 samples analysed in 2024-25.

SAIF-supported research has translated into over 16,210 publications over the seven years (Fig. 5). The publication count rose from 2,152 in 2018-19 to 2,542 in 2022-23, 2,511 in 2023-24 and 2,318 in 2024-25, indicating a growing reliance on SAIF infrastructure for high-impact scientific contributions. Furthermore, SAIF centres have supported a rising number of patentable innovations. These centres enable researchers to validate and refine their ideas

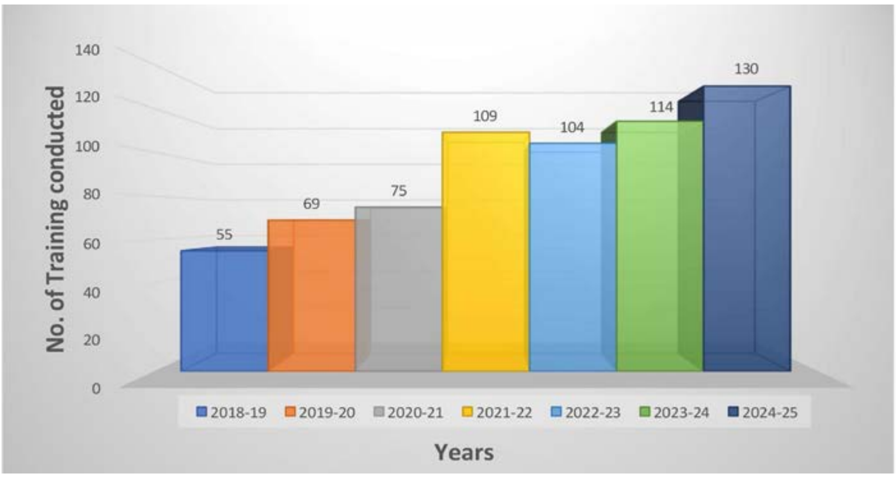

Fig. 6 - Total number of trainings conducted by SAIF centres each year.

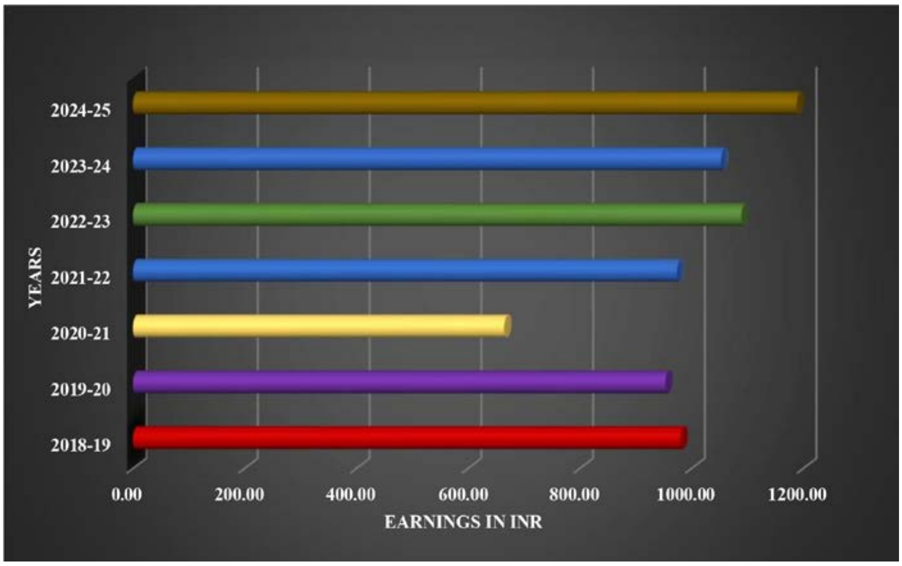

Fig. 7 - Total earning in INR generated by SAIF centres each year.

through advanced instrumentation, thereby contributing to India's improved standing in global innovation indices.

The SAIF scheme is also a major player in scientific capacity building. A total of 656 training programs were organised between 2018 and 2025 (Fig. 6). These programs, conducted in both offline and online modes, covered instrument operation, theoretical principles, and data analysis techniques. With 109 and 130 training sessions in 2021-22 and 2024-25 respectively, the program showed a strong push toward post-pandemic upskilling. These sessions enhanced technical literacy, facilitated networking, and aligned closely with national missions such as Skill India and Atmanirbhar Bharat.

Financial sustainability and operational robustness of the SAIF Programme are reflected in the revenue trends of the centres over the last seven years. Collectively, SAIF centres generated ₹69.11 crore during this period (Fig. 7). However, the COVID-19 pandemic had a pronounced impact on SAIF operations, with widespread closure of academic institutions, constituting a major segment of the user base as well as temporary shutdowns of SAIF facilities themselves. This led to a sharp decline in user access and earnings, which dropped to ₹6.6 crore in 2020–21. Recognising the financial stress faced by the centres in meeting recurring operational expenditures during this period, DST rolled out the SAIF COVID Relief Package to support continuity of operations, salaries of human resources engaged and mitigate pandemic-induced losses. This timely intervention enabled centres to sustain essential services and retain operational readiness. With the gradual resumption of academic and research activities, SAIF revenues rebounded strongly, reaching over ₹11.87 crore in 2024–25. The earnings are predominantly reinvested in equipment maintenance and human resource support, underscoring a well-cycled model of self-sustenance and long-term operational resilience.

Since its inception, around 110 Memoranda of Understanding (MoUs) have been signed by various centres, encompassing both domestic and international collaborations. These MoUs reflect a strong collaborative framework with academic institutions, research organisations, and industry partners, and demonstrate a sustained commitment to fostering national and global cooperation in research, innovation, and capacity building. Notable collaborations include agreements between SAIF, Panjab University, and organisations in South Korea, Denmark, and the USA, which have enabled joint research activities, faculty exchanges, and cross-border sample analyses, thereby significantly enhancing the global visibility and relevance of Indian research.

Societal impact is another critical dimension of the SAIF scheme. SAIF has made significant contributions to academia by offering access to sophisticated instrumentation that individual institutions often cannot afford. This has democratized research capabilities, fostered interdisciplinary collaborations, and strengthened institutional infrastructure. For industries, SAIF offers a cost-effective alternative to in-house analytical setups, aiding in innovation, quality control, and product development. In the health sector, SAIF centres have supported medical research, drug development, diagnostics, and imaging studies. During the COVID-19 pandemic, centres like SAIF Panjab University developed sanitation devices and enabled the distribution of air purifiers to healthcare facilities across the country[13].

In summary, the DST-SAIF scheme has proven to be a resilient, adaptive, and vital component of India's scientific infrastructure. Its impact over the past seven years spans academic excellence, industrial collaboration, healthcare advancement, and global engagement. The scheme's continuous evolution and expansion position it as a model for shared scientific infrastructure, capable of driving India's innovation ecosystem well into the future. Future investments in modernisation, digitisation, and international outreach will ensure that SAIF continues to serve as a beacon of scientific progress in India and beyond.

4. Societal Impact of SAIF

The Department of Science and Technology (DST), Government of India, through its Sophisticated Analytical Instrumentation Facility (SAIF) Scheme, has made a significant impact across multiple sectors. In the following section, the article describes how the SAIF Scheme has fostered contributions to academia, supported industrial research, and advanced the healthcare sector.

4.1. Contributions to Academia and Capacity Building

The SAIF scheme has significantly enriched India's academic landscape by making high-end analytical instruments accessible to researchers. These sophisticated tools, often too costly for individual institutions to acquire, have empowered scientists to pursue cutting-edge research, generate impactful publications, and expand the national knowledge base. This infrastructure has allowed researchers to conduct detailed and high-precision analyses that are critical to scientific discovery and innovation.

Beyond facilitating research, SAIF promotes interdisciplinary collaboration by offering tools that serve diverse fields such as chemistry, biology, physics, and materials science. This integration fosters innovative solutions and encourages knowledge sharing across disciplines, enabling new scientific breakthroughs that transcend traditional academic boundaries.

Training and capacity building are central to the SAIF initiative. Through workshops and hands-on sessions, the scheme equips students, researchers, and faculty with the skills necessary to operate sophisticated instruments and interpret complex data. These efforts have not only strengthened individual expertise but also elevated the collective academic standards in the country. In the area of advanced microscopy in medical sciences, SAIF AIIMS New Delhi has been a leading centre for training and human capacity building for over four decades. Since 1983, the centre has conducted an annual two-week hands-on training programme on electron microscopy of biological specimens for scientific investigators every November–December, with the 41st edition held in November 2025, along with a four-week programme for technical personnel each May–June. To address emerging research needs, the centre introduced a specialized five-day training module on electron tomography in 2022, conducted annually in April[14]. Through these sustained efforts, SAIF AIIMS has trained nearly 600 scientific investigators and about 400 technical staff from across the country, significantly strengthening India's expertise in biomedical imaging and analytical instrumentation.

Furthermore, SAIF's role in enhancing institutional research infrastructure cannot be overstated. The development and upgrading of analytical facilities at participating centers have led to improved research outputs and helped attract national and international collaborations and funding. This infrastructure serves as a foundation for sustainable scientific progress in India.

4.2 Support for Industries

SAIF has also emerged as a vital resource for industrial research and development. Its advanced instrumentation supports innovation and product development across sectors including pharmaceuticals, electronics, textiles, materials science, and nanotechnology. By enabling high-precision analysis and characterization, SAIF centres help industries shorten development cycles and bring innovative products to market faster.

Important strength of the SAIF network are facilities of SAIF Centres which are

NABL-accredited. This accreditation ensures the highest levels of reliability, traceability, and quality assurance in testing and calibration services. For industries, access to NABL-accredited SAIF facilities enhances regulatory compliance, supports certification requirements, and boosts the global acceptability of test data-particularly in export-oriented sectors.

One of SAIF's most valuable offerings to industries is its precision testing and quality-control services. These capabilities ensure compliance with national and international standards, thereby enhancing the credibility and reliability of Indian-made products in the global market.

The shared-infrastructure model also fosters collaboration between academia and industry. These partnerships facilitate the translation of academic research into commercial applications, strengthening innovation ecosystems and contributing to economic development. Joint projects supported by SAIF instrumentation enable technology transfer, prototype validation, and the commercialization of research outputs.

For many industries, outsourcing analytical tasks to SAIF centres is also highly cost-effective. This model eliminates the need for in-house investment in expensive instruments and specialized technical personnel, allowing companies to focus resources on core operations while still accessing world-class, accredited analytical services.

4.3 Specialized Advances in Medical and Health Sciences

The healthcare sector has benefited immensely from the analytical capabilities provided by SAIF. The ability to study biological samples with precision has led to new insights into disease mechanisms, more accurate diagnostics, and better therapeutic strategies. Researchers rely on SAIF tools to conduct experiments that deepen understanding of complex biological systems.

The pharmaceutical industry leverages SAIF facilities throughout the drug development pipeline-from molecular discovery and formulation to stability testing and regulatory validation. These contributions are vital for developing safe, effective, and affordable medications for public health.

In diagnostics and imaging, SAIF instruments support the development of advanced technologies that allow earlier and more accurate detection of diseases. These improvements can lead to timely interventions and improved patient outcomes.

Genomic and proteomic research has also flourished with the support of SAIF infrastructure. Access to high-end tools enables scientists to decode genetic data, study protein interactions, and advance personalized medicine, particularly in the treatment of rare and complex diseases.

The SAIF Centre at AIIMS New Delhi plays a pivotal role in advanced biomedical imaging and diagnostics, offering one of the most comprehensive electron microscopy platforms in the country. Serving over 2,500 research laboratories and clinicians across India, the facility provides an end-to-end workflow from sample preparation to high-resolution imaging, enabling cutting-edge research in biomedical sciences, pathology, virology, nanobiology, and materials science. The centre offers a full suite of scanning and transmission electron microscopy services, including immuno-electron microscopy for ultrastructural localization, disease diagnostics, viral quantification, elemental analysis, STEM, and HAADF imaging. Its specialized infrastructure-comprising multiple ultramicrotomes, TEM block-making systems, sputter coaters, and critical point dryers-is complemented by advanced cryo-EM capabilities such as sample vitrification, cellular cryo-tomography, cryo-ultramicrotomy, and grid screening. Additionally, the facility houses confocal and super-resolution microscopy (SIM and STORM), with biological AFM services to be introduced shortly. Instruments including zeta potential and particle size analyzers, lyophilizers, and HPLC systems further expand its multidisciplinary analytical capacity, positioning SAIF AIIMS as a critical national resource for specialized advances in medical and health-science research.

On the other hand, SAIF Centre at CSIR–Central Drug Research Institute (CDRI), Lucknow, provides advanced analytical and structural capabilities that support national efforts in drug discovery and biomedical research. Equipped with TEM/SEM for ultrastructural studies, LC–MS for analytical method development, and NMR for molecular structure elucidation, the facility also undertakes plant resource exploration, in vitro biosynthesis of natural products, and bioprospecting activities 15. As a critical national resource for advanced drug research and development along with its integrated, multidisciplinary expertise and modern instrumentation, SAIF CDRI has become a key national resource for high-quality research and affordable healthcare innovation. During the COVID-19 pandemic, SAIF centers demonstrated their agility and relevance. Despite lockdowns, many centers remained operational, ensuring continuity in critical research. SAIF Panjab University played a pioneering role by developing ultraviolet sanitization chambers and currency disinfectors. These innovations were deployed across multiple institutions and administrative bodies to enhance safety. Additionally, a vehicle purging system was introduced to sanitize interiors and reduce pathogen load, addressing both health and air quality concerns.

In partnership with Molekule Inc., SAIF Panjab University distributed over 3,000 air purifiers to hospitals across India during the second wave. This initiative not only aided in infection control but also exemplified how research infrastructure can directly contribute to public welfare during crises.

5. Bibliometric Analysis Methodology in publication trends

A bibliometric search was conducted using the **Web of Science Core Collection** database to quantify and assess the research output associated with Sophisticated Analytical Instrument Facilities (SAIF) and related instrumentation centers in India. The search strategy employed a comprehensive set of keywords covering full names, abbreviations, and institutional variations of SAIF facilities across major universities and national institutes. The search string included terms such as "*SAIF*," "*Sophisticated Analytical Instrument Facility*," "*SAIF IIT Madras*," "*SAIF Panjab University*," "*SAIF & CIL*", "*STIC CUSAT*", "*SAIF IIT Bombay*", and other recognized institutional affiliations, along with proximity operators (e.g., NEAR/5) to ensure retrieval of contextually relevant records. The search was executed in the **Full Text (FT)** field to capture publications acknowledging SAIF support. This query identified **16,990 records**, forming the dataset for further bibliometric assessment including publication trends, authorship patterns, collaborative networks, citation impact, and research thematic analysis.

The bibliometric analysis of 16,990 publications retrieved from the Web of Science Core Collection demonstrates a broad disciplinary distribution of research outputs associated with SAIF-supported facilities in India. The majority of publications are concentrated in **Chemistry and Materials Science–related domains**, reflecting the instrumental strengths and service priorities of SAIF centers. Chemistry Multidisciplinary accounts for the largest share with **18.17% (n = 3,087)** of the total records, followed closely by *Materials Science Multidisciplinary* with **16.65% (n = 2,828)**. Other major contributing fields include *Physical Chemistry* **(13.64%)** and *Organic Chemistry* **(11.48%)**, together representing nearly half of the entire dataset. Additionally, significant contributions are observed in *Applied Physics* **(7.42%)**, *Inorganic and Nuclear Chemistry* **(6.78%)**, and *Condensed Matter Physics* **(5.55%)**, indicating strong interdisciplinary engagement.

Emerging and application-oriented fields such as *Nanoscience & Nanotechnology* **(4.69%)**, *Chemical Engineering* **(4.39%)**, *Biochemistry & Molecular Biology* **(4.38%)**, and *Medicinal Chemistry* **(4.22%)** also show substantial representation, underscoring the role of SAIF facilities in supporting advanced and translational research. Contributions in areas including *Polymer Science, Environmental Sciences, Energy & Fuels, and Electrochemistry* further highlight the diverse utilization of high-end analytical instrumentation across scientific domains. Overall, the category-wise distribution confirms that SAIF centers support a *wide spectrum of research disciplines*, with a clear dominance in the chemical sciences, while also fostering growth in interdisciplinary and emerging scientific fields.

6. Contemporary Thematic Research Areas at SAIF Centres: Catalyzing Innovation in Science and Technology

The Sophisticated Analytical Instrument Facilities (SAIF) centers, supported by the Department of Science and Technology (DST), are actively engaged in cutting-edge and contemporary research across diverse thematic areas that align with national priorities and global scientific trends. For instance, SAIF Gujarat emphasizes value addition from renewable resources, bio-remediation of toxic elements, and the synthesis and application of heterocyclic compounds-crucial for sustainable industrial processes. SAIF Guwahati focuses on geochemical applications of XRF data and innovations in green energy and sustainable chemistry, while SAIF Kottayam addresses emerging concerns like chemical pollutants and protein-pollutant interactions in water systems, advancing research in oxidation technologies and environmental safety. SAIF IIT Bombay's thrust on nanomaterials, quantum dots, and advanced metabolomic analyses supports the growing demand in energy, materials science, and biomedical diagnostics.

In parallel, SAIF Dharwad integrates nanotechnology with healthcare and environmental sciences, tackling key challenges in drug delivery, ecotoxicology, and reproductive biology. SAIF Chandigarh and SAIF Lucknow contribute significantly to pharmaceutical sciences, with a focus on nanotechnology, herbal medicine quality control, and drug discovery. SAIF Kochi and SAIF Kolhapur play pivotal roles in material science and environmental monitoring, with expertise in microscopy, XRD, and green hydrogen production. Furthermore, SAIF NEHU supports multidisciplinary research in chemical synthesis, environmental science, and nanotechnology, whereas SAIF IIT Madras excels in structural and spectroscopic analysis, offering advanced techniques like XRD, NMR, and hyphenated mass spectrometry systems. Collectively, these centers form a robust national infrastructure for advanced instrumentation and domain-specific research, directly contributing to India's innovation ecosystem in health, environment, and sustainable technology.

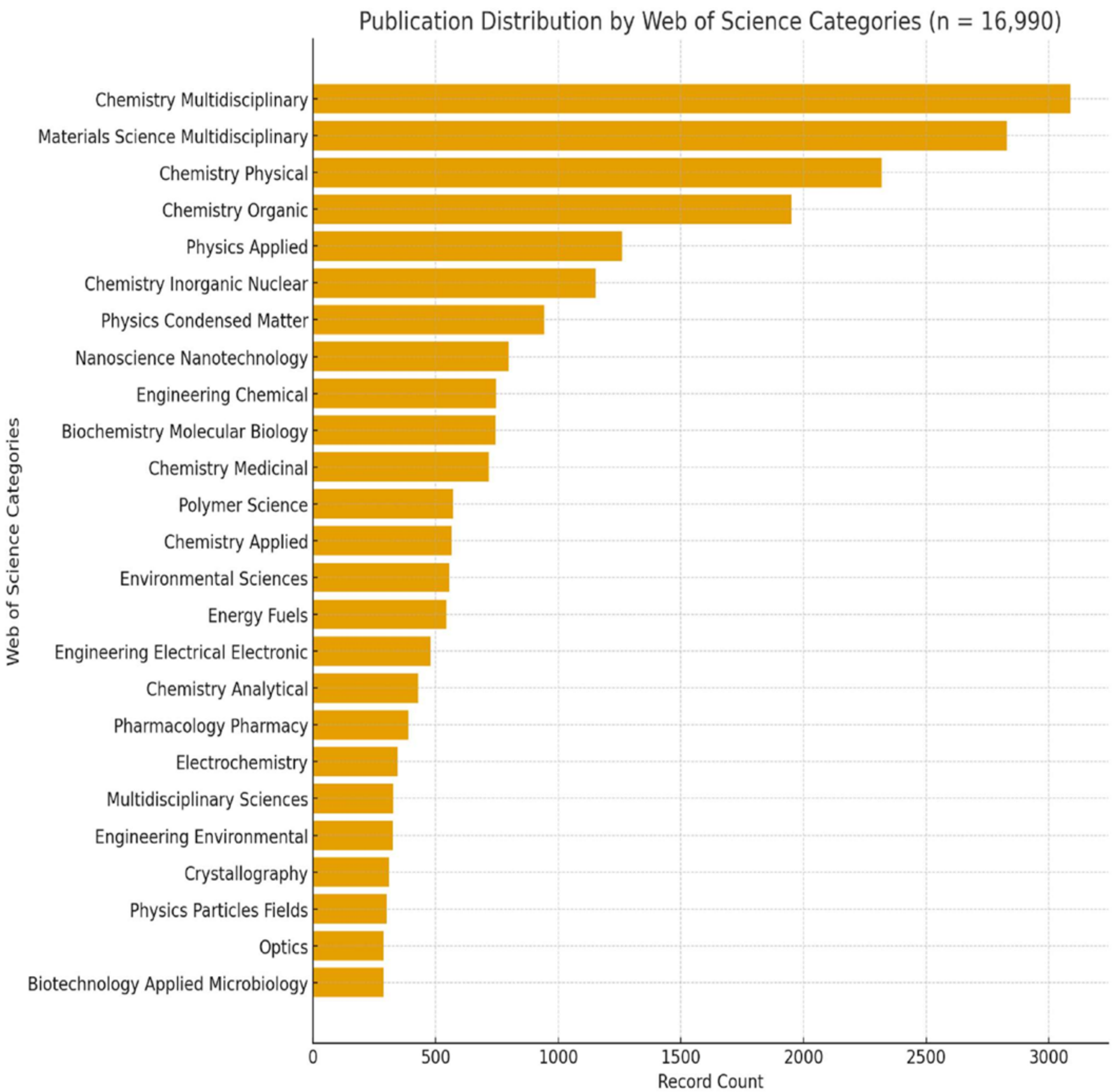

Fig. 8 - Bibliometric Analysis of Publications Retrieved From the Web of Science Core Collection

7. Conclusion and Way Forward

Launched in 1974, the Sophisticated Analytical Instrumentation Facility (SAIF) scheme of the Department of Science and Technology (DST) has expanded to 15 centres across India. Over the past seven years, DST-SAIF has played a crucial role in advancing scientific research and innovation, serving more than 1,30,000 users and facilitating the analysis of nearly 7,50,000 samples across diverse disciplines. Beyond providing analytical services, SAIF has emphasized training and capacity building, contributing to the development of a skilled scientific workforce. The scheme has also supported high-impact publications, intellectual property generation, and industrial product innovation. Its societal impact is evident through its contributions to academia, industry, and public health, particularly during the COVID-19 pandemic.

The SAIF model aligns closely with international practices in countries possessing strong research infrastructures. In Germany, shared instrumentation facilities operated by institutions such as the Max Planck Institutes and the Helmholtz Association promote collaborative research through centralized, government-funded infrastructure. Similarly, in the United States, agencies such as the National Institutes of Health (NIH) and the National Science Foundation (NSF) support national user facilities through organizations like the National User Facility Organization (NUFO), providing advanced tools and expertise to the broader research community. Comparable national platforms exist in Russia and China, where government-supported research centres and centralized instrumentation systems facilitate access to sophisticated equipment for both basic and applied research. These international systems emphasize collaboration, training, and large-scale resource sharing. In India, complementary initiatives such as the I-STEM web portal, ICMR's I-RISE infrastructure sharing system, and the SRIMAN guidelines have further strengthened access to research infrastructure. Within this ecosystem, the SAIF scheme remains a core pillar, democratizing access to high-end instrumentation and fostering a culture of shared scientific growth. By enabling access to world-class facilities and promoting collaboration, SAIF continues to drive scientific discovery and national development, while its alignment with global best practices enhances India's position in research infrastructure sharing.

As India's scientific and academic landscape expands with over 1,200 universities and university level institutions, including IITs, NITs, and IISERs, and more than 50,000 colleges the demand for advanced research infrastructure is increasing rapidly. To address these needs, the SAIF programme should prioritize the establishment of additional centres equipped with a wider range of specialized instruments and ensure broader geographical coverage, particularly in underserved regions. Strengthening linkages with industry and MSMEs will be essential to enhance translational research, product development, and problem-solving capabilities. Increasing the number of NABL-accredited SAIF laboratories will further build industry confidence by ensuring reliable and standards-compliant analytical services. Improved integration of SAIF facilities with the I-STEM portal will enhance visibility, streamline access, and optimize nationwide utilization. Together, these measures will enable SAIF to evolve into a more inclusive, industry-responsive, and future-ready national research infrastructure network.

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Memberships of INAE

Connecting Academia, Industry & Engineering Professionals

The Indian National Academy of Engineering (INAE), a premier Academy, dedicated to the advancement of engineering and technology in India, offers three primary categories of membership-Institutional Membership, Corporate Membership, and Individual Membership. These membership types are designed to bring together academia, industry, and the professional engineering community, encouraging collaboration, innovation, and thought leadership in engineering-related fields. To have a wider reach and participation of engineering community, these new streams of membership of INAE have been instituted recently.

Institutional Membership

Institutional Membership of INAE is offered to academic and research institutions, including universities, colleges, engineering institutes and R&D organizations that are actively engaged in scientific and technological pursuits. This membership category is aimed at strengthening linkages between INAE and institutions that contribute significantly to engineering education, research, and innovation. Institutional Members benefit from opportunities to participate in national conferences, symposia, and technical events organized by INAE. They also receive access to a wide range of INAE publications, policy papers, and technical reports, and gain opportunities to collaborate on engineering initiatives and national missions. This membership serves as a platform for institutions to contribute to shaping the national engineering agenda and to engage with a larger network of experts and decision-makers.

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Individual Membership

Though the Fellowship of INAE is the gold standard of recognition for notable engineers, who are elected by a rigorous three-tier process by expert committees of the Fellowship, however, in order to encourage a wider reach and participation of engineering community, Individual Membership has been recently introduced at INAE. The Individual Membership is accorded to professionals working in engineering and technology in industry, R&D or academic institutions, engineering services, entrepreneurship firms and government/private agencies by a selection process. All Individual Members benefit from recognition by the Academy and provides a platform for networking opportunities. A special program 'Technology Conclave' has been curated for the Members of INAE. Members are also invited for the INAE's flagship events held every year.

INAE currently offers Senior and Associate Memberships, to engage engineers at different stages of their careers. Senior Membership is awarded to experienced professionals with significant experience in engineering community. Associate Membership is aimed at promising mid-career engineers with opportunities for participation in INAE activities. Together, these categories support a structured growth pathway within India's engineering ecosystem.

INAE's membership structure is designed to build a vibrant, interconnected community of institutions, companies, and individuals who are committed to advancing engineering and technology for national development. Through its diverse membership base, INAE fosters interdisciplinary collaboration, provides a platform for dialogue on critical technological issues and promotes excellence in engineering practice and education across India and beyond.

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A significant new initiative launched by INAE is the quarterly e-Magazine TechFrontier, conceived to showcase emerging trends, impactful research, and technological innovations in engineering and technology. The magazine was successfully launched on April 20, 2025, during the INAE Foundation Day.

This digital publication is envisioned as a platform to highlight cutting-edge advancements from India and across the globe. Its objective is to create awareness about engineering and technology by publishing articles on futuristic, emerging, and high-impact technologies that appeal not only to the engineering community but also to readers outside the field who have an interest in science and technology.

Volume I, Issue I of INAE TechFrontier, centred on the theme "Quantum Technology: India-centric Policy Perspectives", was successfully launched on April 20, 2025, during the INAE Foundation Day function held at IIT Delhi. The inaugural issue received an encouraging response and set a strong precedent for future editions. The issue features invited articles highlighting indigenous products, technological breakthroughs, and conceptual or review contributions that collectively reflect the cutting-edge advancements taking place in the country in the field of quantum technology.

Click/Scan for TechFrontier Volume I, Issue I

Volume I, Issue II of INAE TechFrontier focuses on the theme "Manufacturing", a sector that forms the backbone of India's aspirations for technological self-reliance, global competitiveness, and sustained economic growth. As the nation advances toward becoming a major innovation-driven economy, the manufacturing ecosystem encompassing advanced materials, automation, digitalisation, and sustainable production continue to evolve rapidly.

This edition features a thoughtfully curated collection of insightful articles that showcase the diversity, depth, and transformative potential of manufacturing-related research and development underway across the country.

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Volume I, Issue III, of INAE TechFrontier focuses on the theme "Cyber-Physical Systems", a rapidly evolving domain that integrates computation, communication, and control to transform sectors ranging from manufacturing and healthcare to transportation and industrial automation. The curated articles in this issue offer diverse perspectives on how Cyber-Physical Systems are reshaping industries, enabling intelligent and interconnected systems, and driving next-generation engineering solutions.

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Volume I, Issue IV of INAE TechFrontier, centred on the theme "Sustainability of Civil Infrastructure", The articles in this issue collectively explore innovative design approaches, climate-responsive strategies, advanced foundation systems, and low-carbon materials, offering valuable insights into building sustainable and durable infrastructure for the future.

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About INAE:

The Indian National Academy of Engineering (INAE), founded on April 20, 1987 as a Society under the Societies Registration Act, is an autonomous professional body located at Technology Bhawan, New Delhi. It comprises India's most distinguished engineers, engineer-scientists and technologists covering the entire spectrum of engineering disciplines. INAE functions as an apex body and promotes the practice of engineering & technology and the related sciences for their application to solving problems of national importance. The Academy also provides a forum for futuristic planning for country's development requiring engineering and technological inputs and brings together specialists from such fields as may be necessary for comprehensive solutions to the needs of the country. The actionable recommendations emanating from the deliberations of technical events and programs are submitted to the concerned government Departments/Agencies for consideration as inputs for framing of national policies. As the only engineering Academy of the country, INAE represents India at the International Council of Academies of Engineering and Technological Sciences (CAETS); a premier non-governmental international organization comprising of Member Academies from 31 countries across the world, with the objective of contributing to the advancement of engineering and technological sciences to promote sustainable economic growth.

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